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Essays on Private Intermediation in Matching Markets

with applications to Online Listing Services and Real Estate Brokerage

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General introduction

Many transactions in matching markets happen through private intermediaries. Examples of intermediate service providers are online listing platforms and real estate brokers in real estate markets, online job boards, temporary help agencies and recruitment agencies in the labor market, and online dating platforms in the dating market. This dissertation analyzes - both theoretically and empirically - the profit maximizing behavior of these intermediaries and evaluates the market distortions that can emerge from this behavior. It is particularly relevant to evaluate the business models used by these type of intermediaries today, given that the nature of matching markets has drastically been changing over the past two decades. More specifically, the rise of the internet resulted in a vast increase in information availability in these markets.

On the one hand, the internet has led to the development of a “new” type of intermediaries: online listing platforms who offer a matching service in return for a flat fee. These online platforms have largely substituted for informal search channels and local newspapers and they take up a dominant position in most matching markets today. To illustrate this, Manning (2011) reports for the UK that the percentage of unemployed (employed) job-seekers using the internet rose from 48% (62%) in 2005 to 79% (82%) in 2009. Similarly, Kuhn and Mansour (2014) report for the US that between 2000 and 2009, the share of young, unemployed workers who used the internet to look for work tripled, from 24 to 74%. The same story holds for real estate markets: the National Association of Realtors (2012) reports for the US in 2012 that 90% of buyers used the internet in their home search and 93% of sellers state that their home was listed or advertised on the Internet.

On the other hand, the increased information availability has forced "incumbent" intermediaries to adjust their business strategies. In real estate brokerage, for example, the new technologies had a significant impact on the nature of competition among brokers. Previously, real estate agents relied heavily on their competitors to offer an efficient matching service by sharing information about local real estate markets. A consequence of this collaboration was that it led to apparent collusive broker behavior in pricing their services. In the US, for example, throughout most of the 20th century brokers charged a fixed commission rate of 6%, independent of the number of competitors within a local market. These traditional information systems, however, are severely under pressure today. Brokers rely less heavily on their colleagues to establish valuable real estate transactions which has led brokers to deviate from offering the traditional service packages and from the conventional fixed commission rates (see, for example, the USDOJ-FTC (2007) report on the US brokerage industry for a detailed discussion on this transition).

This dissertation evaluates both the behavior of online intermediaries taking into account the particularities of their novel matching technologies, as well as that of the more traditional matchmakers taking into account the changed environment in which they operate. To do this, the dissertation is divided into four chapters. The first chapter is purely theoretical and models the optimal pricing behavior of a monopoly platform that operates in a matching market and that charges a flat participation fee to users on both sides of the market. The second chapter extends this model and makes specific assumptions to account for the particularities of online listing service platforms. This model is then taken to the data to estimate the market distortions that result from the pricing behavior of a large online real estate advertisement platform in Belgium. The third chapter again presents theory on optimal pricing by a matchmaker that is now allowed to charge a fee proportional to an observed component of the match valuation between matched participants (like the sales price of a real estate property or the wage of a worker). Finally, the fourth chapter again imposes specific assumptions to account for the particularities of real estate brokerage services and extends the model to imperfect broker competition in setting the commission rate charged for their service. This model is then taken to the data to test for market efficiency in the Belgian real estate brokerage industry. The remainder of this introduction presents a more detailed summary of each of the four chapters.

Chapter 1: Monopoly flat fee pricing and market distortions

This theoretical piece of work builds on the literature of two-sided markets (e.g. Rochet and Tirole (2003), Weyl (2010)) to evaluate the optimal pricing behavior of platforms that operate in one-to-one matching markets, emphasizing the role of the network externalities typically present in these type of markets. More specifically, the existing models of two-sided markets explain why platforms charge different prices to different groups of participants. Generally, the platform will subsidize participation on a side of the market the higher is that side's positive cross-side externality to users on the other side of the market. However, in matching markets there also exists a negative own-side congestion externality that the platform internalizes by taxing users for its presence.

Assuming a monopoly platform pricing model, the first contribution of this chapter is to show that these positive cross-side and negative own-side externalities can be summarized by the matching elasticity derived from a general matching function (e.g. Petrongolo and Pissarides (2001)) that captures the efficiency of the platform's matching technology. The platform charges a lower price to a side of the market the higher is that side's matching elasticity. The second contribution is to show that the platform's pricing strategy only partially internalizes the efficiency of its matching technology, compared to the social optimum. In particular, the possibility is discussed that a monopoly matchmaker sets too *high* a price on the low-price side of the market and too *low* a price on the high-price side of the market, resulting in insufficient inequality in prices from a social point of view.

Chapter 2: Market distortions in online real estate advertisement pricing

This chapter aims to empirically apply the framework presented in the first chapter and test for the efficiency of the pricing behavior of a private online real estate listing platform. The results in the first chapter were derived for general preferences of participants and a general platform matching technology. In contrast, the present chapter makes explicit assumptions on this, tailored for a listing service platform that operates in a real estate market. For example, matched participants are allowed to bargain over the division of the match surplus, such that the sales price of a property becomes an endogenous outcome variable. In addition, the matching technology is modeled such that it accounts for the asymmetries inherent to the presence of a "listing-side" (sellers) and "searching-side" (buyers) on the platform. This way the socially optimal fees charged to sellers and buyers can be derived in terms of parameter values that are either observable or can be estimated. These counterfactual fees can then be compared to the observed fees in practice.

Combining data on the number of listings and their online duration on a large online listing platform with administrative data on the total amount of real estate sales in Belgium in 2013 yields a proxy for the efficiency of the matching technology offered by the platform. In addition, by imposing specific assumptions on the distributions of buyer and seller preference parameters, these can be estimated from the distribution of ask-prices available from a large sample of listings, combined with other detailed listing characteristics. The resulting estimates for the socially optimal fees suggest that the observed fees in practice are significantly *below* the socially optimal levels. The reason for this is that the negative externalities that inherently arise from the matching and bargaining process among buyers and sellers are currently insufficiently internalized in the service fees charged to buyers and sellers compared to the social optimum. This result sharply contrasts the conventional result for standard product markets that firm market power unambiguously results in upwardly distorted prices.

Chapter 3: Proportional service fees as a selection tool

The first two chapters of this dissertation analyze matchmakers that charge a flat fee in return for their services, which applies well to the "new" type of online intermediaries, as described above. However, the "incumbent" or more traditional intermediaries typically charge fees proportional to an observed component of the match valuation of matched participants. Examples are real estate brokers that charge a commission proportional to the sales price of a property and recruitment agencies that charge a fee proportional to the wage of a placed worker. This chapter tackles the question why some intermediaries charge a proportional service fee in return for their services, some a flat fee and some a combination of both. To do so, a monopoly pricing model is presented in which a service provider attracts consumers allowed to be heterogeneous in two dimensions. One dimension of consumer types always remains private information. The other consumer type, however, is assumed to become revealed to the monopolist once the service is provided and a fee can be charged proportional to its revealed value on top of a flat service fee.

It is shown that the service provider only makes use of a proportional service fee if its use induces "advantageous selection" of consumers into the market. That is, when the consumers with the highest observable types are also the ones with the highest willingness to pay for the service. In addition, the monopolist exclusively uses a proportional fee and no flat fee when the advantageous selection effect outweighs an "adverse sorting" effect at the margin, which is inherent to the use of this fee type. In terms of welfare, it is shown that a Pigouvian planner never charges a proportional service fee because it has an inefficient misallocation effect, familiar from the third degree price-discrimination literature. Furthermore, it is demonstrated that allowing a monopolist to use of a proportional fee has very similar welfare effects as allowing for third-degree price discrimination.

Chapter 4: Competitive service fees, free entry and social efficiency in real estate brokerage markets

It is well-known from the literature that a lack of price competition in setting commission rates combined with limited entry constraints for new brokers to enter local real estate markets can result in significant social waste (e.g. Hsieh and Moretti (2003)). As argued above, however, over the past two decades the landscape of real estate brokerage markets has been changing by the emergence of new information technologies, which resulted in intensified price competition among brokers. It is therefore important to investigate market efficiency under imperfect broker competition, rather than assuming the absence of price competition as in most of the existing literature.

This chapter presents a model of imperfect competition among brokers that operate in a market for real estate and charge a service fee to sellers, that consists of flat and proportional component and is allowed to be imperfectly passed through to buyers through an asymmetric Nash bargain over the sale price of the traded real estate properties. In this setting it is shown that there exists an inverse u-shaped relationship between the degree of price competition among brokers in setting their service fees and social value generated in the market. This because the presence uncertainty about the bargaining outcomes when participants enter the market results in negative participation externalities, which should be internalized in the broker service fees. Thus neither monopoly (broker collusion) nor Bertrand, but an intermediate degree of price competition is optimal from a social point of view. In addition, in the presence of fixed entry costs and free broker entry, the familiar result that free broker entry always results in excessive entry from a social point of view (e.g. Mankiw and Whinston (1986), Hsieh and Moretti (2003)) is confirmed in the present setting.

Both findings combined, that marginal cost pricing is not efficient and that entry is always excessive, has important implications for the effectiveness of different policy instruments that can be used should a social planner want to regulate the market to establish the social optimum. When the observed service fee is *below* the socially optimal level, regulating the service fee brokers are allowed to charge will result in a conflict of interest. Raising the fee will bring it closer to its desired level, but it will also worsen the entry distortion because a higher markup for a given fixed cost will incentivize more brokers to enter the market. In this case, it is preferable the regulate broker entry, given that restricting the number of brokers allowed to operate the market will both raise the service fee and mitigate the entry distortion. In contrast, when the observed service fee is *above* the socially optimal level (for example due to broker collusion), the opposite policy recommendation holds. Restricting entry will mitigate the entry distortion, but will also undesirably further raise the service fee or leave it unaffected. In contrast, regulating the service fee in this case can again mitigate both distortions at the same time, given that for a lower service fee some brokers will be forced to exit the market.

The model is then taken to the data on the Belgian market for real estate brokerage. Based on estimated parameter values derived from the data, several welfare counterfactuals are constructed to evaluate the effectiveness of the different policy instruments that can possibly be used by a social planner. Given that in the observed equilibrium the average service fee is below the social optimum, entry regulation is predicted to yield a welfare gain of about 20%. In contrast, regulating the service fee, neglecting the entry effect, would result is a welfare *loss* of about 40%. These results illustrate the importance of making the proper choice of which policy instrument to use should a policymaker aspire to intervene in a real estate brokerage market.

Chapter 1

Monopoly flat fee pricing and market distortions[1]

1 Introduction

This chapter presents a model of how a private intermediary that operates as a matchmaker in a one-to-one matching market should optimally price its services when charging a flat fee to both sides of the market. This pricing behavior is then compared to that of a social planner to evaluate the potential market distortions that can arise in this setting. The model forms the basis for the theory used in all subsequent chapters, which either extend the model or impose more specific assumptions, depending on the application at hand.

The model emphasizes the specific role of the network externalities that are typically present in matching markets. For example, the probability for an individual worker to find a job through an online job board decreases when there are more job-seekers and fewer vacancies. Similarly, a realtor may find it difficult to sell one's home when rivalry among sellers is fierce and the task is likely to be easier when there are more potential buyers searching for a property. In other words, a matching technology is typically

[1] This chapter is based on the article "Platform Pricing in Matching Markets" published in the Review of Network Economics, 2014, 12(4): 437–457, jointly with Maarten Goos and Patrick Van Cayseele.

characterized by important congestion or negative own-side network externalities and by positive cross-side network externalities.

To investigate how platforms account for network externalities when charging different prices between sides of the market has precisely been the focus of a recent strand of literature, referred to as the "two-sided markets" literature (see, among others, Caillaud and Jullien (2003), Rochet and Tirole (2003, 2006), Armstrong (2006), Weyl (2010))[2]. Generally, the platform's price to one side of the market will be lower the larger is that side's positive cross-side externality to users on the other side of the market. For example, when one side of the market only differs in that there are more users, the platform will charge this side a lower price because it is easier for users on the other side to trade. However, matching markets are also characterized by a negative own-side congestion externality. This because the realization of a worker-firm match, for example, implies that this vacancy is no longer available to other job-seekers and that this worker is no longer employable at other firms.

To formally analyze the different incentives that a matchmaking platform has in its pricing behavior, this chapter first introduces a general matching function – a concept well-known from the labor economics literature (see, for example, Petrongolo and Pissarides (2001) for a review)[3] – that captures the platform's matching technology. The matching technology is said to be more efficient for a side of the market when the negative own-side

[2] See Rysman (2009) and Evans and Schmalensee (2013) for recent surveys on the two-sided markets literature.
[3] Also see Pissarides (2000) and Rogerson, Shimer and Wright (2005) for overviews of how the matching function is put to work in labor market theory and applications.

externality – which is expressed in absolute value throughout the analysis – is small and the positive cross-side externality is large. It is shown that the platform's matching efficiency for a side of the market can be meaningfully summarized by that side's matching elasticity, defined as the percentage increase in total matches for a percentage increase in own-side participation. That is, a smaller negative own-side and larger positive cross-side externality – or a more efficient matching technology – implies a higher matching elasticity for that side of the platform.

The first contribution of this chapter is to show that the optimal price charged by a monopoly matchmaker to a side of the market is lower when that side's matching elasticity is higher. The intuition for this result is simple. A higher matching elasticity results from a smaller negative own-side and a larger positive cross-side externality. Because this gives the monopoly matchmaker less of an incentive to tax the negative own-side effect and more of an incentive to subsidize the positive cross-side externality, its price will be lower. Consistently, it is shown that in a symmetric setting in which two sides differ only in their matching elasticities, the monopoly matchmaker charges a lower price to the side that has the highest matching elasticity.

The second contribution of this chapter is to show that a monopoly matchmaker only partially internalizes the efficiency of its matching technology compared to the incentives of a social planner. More specifically, a higher matching elasticity leads to a larger difference between the private platform's and socially optimal price. The intuition for this is the following. A higher matching elasticity decreases the profit maximizing price which increases participation by marginal users. However, these marginal users value the platform’s service less than the average user. This heterogeneity in user types gives the private platform an incentive to discourage participation by charging a higher price compared to a social maximizer that internalizes the matching externalities through their average and not marginal user valuations. In addition to this, a relationship is derived between the matching technology and price distortions between sides of the platform. In particular, it is shown that a monopoly matchmaker could set too low a price on the high-price side of the market and too high a price on the low-price side of the market, resulting in inequality in prices between sides of the platform that is too low from a social point of view. To illustrate this case, realistic parameter values are assumed for lognormally distributed heterogeneity in user types and a constant returns to scale matching function.

In the literature, various other contributions have recently been made on the topic of optimal pricing by matching platforms. Closest related is Chen and Huang (2012) who consider a specific matching technology where sellers post the price for their goods to attract buyers and buyers choose sellers. They analyze optimal platform pricing in this setting and show that the seller-side of the market is never subsidized by a private platform. To compare, the model presented here does not analyze the possibility that platform fees are passed through by sellers in the price of a good and the matching technology is more general than the one assumed in their model, which allows to derive a general relationship between the price charged on each side and that side’s matching elasticity. Their result that sellers are never subsidized is consistent with the present model when the seller-side of the market has the lowest matching elasticity. In chapter 2 of this dissertation, a specific listing technology is analyzed which confirms that the “listing-side” of the market (i.e. sellers) indeed have a lower matching elasticity than buyers by nature of the listing technology and hence are charged a higher fee.

Also closely related is the study of Niedermayer and Shneyerov (2013) who analyze optimal platform pricing in a dynamic random matching model with buyer-seller bargaining. They show that under a symmetric matching technology, asymmetric bargaining weights results in asymmetric optimal platform fees and suggest that the presence of a monopoly intermediary in a search market can be welfare enhancing. In contrast, the present chapter has exogenous valuations for buyers and sellers and ignores certain bargaining issues to focus on the market distortions that potentially emerge from an asymmetric matching technology.

In addition, Damiano and Li (2007, 2008) explore the sorting role of optimal pricing by a private monopolist and by duopolists under user “quality” differentiation. Gomes and Pavan (2014) further extend the model to allow for many-to-many matching. In contrast, the model presented here abstract from complementarities between user types such that sorting of users plays no role and the platform is not allowed to price discriminate within user groups. Instead, the focus here is on the network externalities linked to the matching technology.

Finally, Ellison and Fudenberg (2003) propose a general framework to analyze how the joint presence of cross- and own-side network externalities affects the market participation decision of two types of user groups. They do not explicitly analyze, however, the optimal pricing behavior of platforms. Belleflamme and Toulemonde (2009), among others, do analyze the impact of both network effects on optimal platform behavior, but not in a setting of one-to-one matching as in the present chapter.[4]

The remainder of the chapter is organized as follows. Section 2 presents the framework of a monopoly matchmaker where network externalities are captured by a matching function that generally characterizes the platform's matching technology. Section 3 shows how the platform's optimal prices depend on the platform's matching technology, and Section 4 examines implications for welfare. Section 5 concludes.

2 Framework

2.1 User preferences and demand

Consider a platform that connects two types of user groups $I = B, S$. One can think of side B as being buyers and side S as being sellers of a real estate property or any other good for which trade between participants on the two sides of the market is exclusive, that is, if two users are matched they cannot match with any other users. For a labor market, one can think of B as being workers and S as being firms. When users on side I participate they have a probability $0 \leq m^I \leq 1$ of being matched, assumed to be the same for all

[4] Other contributions that evaluate the impact of own-side externalities on the behavior of platforms in different settings are, for example, Reisinger, Ressner and Schmidtke (2009), Viecens (2009), Anderson and de Palma (2009) and Casadesus-Masanell and Halaburda (2014).

users on the same side but allowed to differ across sides – these matching probabilities are further characterized in the next subsection.

Users on side I are heterogeneous in two dimensions: V^I denotes the valuation of an I-side user when matched and Z^I when unmatched. For example, the match valuation V^B could be the valuation of a buyer for a real estate property, net of the price the buyer expects to pay for the property, or it could be the wage a job-seeker expects to get when finding a job through the platform. Similarly, V^S could be the price a home-seller expects to receive, net of any costs of providing the good to the market, or it could be the revenue a firm expects to make from hiring a worker, net of the wage the firm has to pay. The outside option Z^B could be the net valuation a buyer expects to receive when purchasing the good through an alternative platform, or the disutility of not purchasing at all (in which case Z^B might be negative), or it could be the job-seeker's reservation wage of accepting a job through the platform or its unemployment benefit. Finally, Z^S could be the expected gains of selling through an alternative matchmaker or the mortgage cost for the home-owner when not selling, or it could be the opportunity cost to a firm of not hiring a worker through the platform. Note these valuations of users are considered as exogenous in this chapter and the description is deliberately kept a bit vague such that any interpretation is feasible at this point. The following chapters will impose more specific assumptions these preferences.

The platform charges a flat fee for the matching service, which is allowed to differ across the two sides of the market, but is the same to all participants within sides. The price is modeled as a per-match fee p^I which is paid by participants conditional on being matched. Note that the price can equivalently be modeled as a participation fee P^I which is paid by users when they enter the platform by simply substituting for $p^I = P^I/m^I$ in all expressions below. It is convenient, however, to display the analysis in terms of per-match fees because it simplifies notation. Further note that the equivalence between the two fee types might not necessarily hold in practice. For example, it could be costly to monitor matching outcomes such that the platform would prefer charging participation over per-match fees. Appendix 1.A at the end of this chapter discusses the assumptions underlying the equivalence in greater detail and elaborates on cases for which it no longer holds.

In the setting described, expected utility for a user on side I of the platform equals:

$$U^I = (V^I - p^I)m^I + Z^I(1 - m^I) \tag{1}$$

Expected utility net of the outside option, defined as $u^I \equiv U^I - Z^I$, can then be written as:

$$u^I = (v^I - p^I)m^I \tag{2}$$

in which $v^I \equiv V^I - Z^I$ is defined as the net match valuation. Users participate at the platform when their expected net utility is positive, i.e. when $u^I \geq 0$.[5]

[5] Note that the participation decision only depends on a single source of user heterogeneity, i.e. a user's net match valuation v^I. This simplification follows from the assumptions that users are risk neutral and that they differ in their outside options rather than in their fixed benefits of using the platform as is assumed in, among others, Armstrong (2006), Rochet and Tirole (2006) and Weyl (2010).

Finally, assume that the net match valuation v^I is distributed by a twice continuously differentiable distribution function $F^I(.)$ and density function $f^I(.)$ that are public information. When the mass of potential participants is normalized to unity, the fraction of participating users on side I of the platform is given by:

$$N^I = 1 - F^I(p^I) \tag{3}$$

2.2 The matching function and matching elasticities

If N^B users participate on side B and N^S users participate on side S of the platform, assume that the total amount of matches is given by the well-known matching function $M = M(N^B, N^S)$. The advantage of introducing this matching function is that it allows us to account for the efficiency of the matching technology without having to make explicit the imperfections in the matching process. Also assume that the platform is a random matchmaker such that all participants on the same side have the same probability of being matched:

$$m^I = M/N^I \tag{4}$$

As is standard in the matching literature, the matching function $M(N^B, N^S)$ is assumed to be (i) twice continuously differentiable; (ii) weakly increasing; (iii) weakly concave; and to have that (iv) $M(N^B, 0) = M(0, N^S) = 0$; (v) $M \leq min[N^B, N^S]$. Under these weak regularity conditions, it is easy to show that the match probability $m^I = M(N^I, N^J)/N^I$ (with J the other side than I) is weakly decreasing in own-side participation N^I which captures a negative own-side externality, and weakly increasing in cross-side participation N^J which captures a positive cross-side externality.

A useful way to summarize the negative own-side and positive cross-side externalities in the matching technology is through the matching elasticity for side I:

$$\phi^I \equiv \frac{\partial M}{\partial N^I} \frac{N^I}{M} \tag{5}$$

with $0 \leq \phi^I \leq 1$. The matching elasticity for side I is defined as the percentage increase in the total amount of matches for a percentage increase in own-side participation. Importantly, there is a one-to-one relationship between the negative own-side and positive cross-side externalities and the matching elasticity. To see this, note that the negative own-side externality per-match is given by:

$$\left| N^I \frac{\partial m^I}{\partial N^I} \frac{1}{m^I} \right| = 1 - \phi^I \tag{6}$$

which is the absolute value of the sum across N^I participants (which gives the term N^I) of the decrease in their match probability when another I-side user enters the platform (which gives the term $\partial m^I / \partial N^I$) rescaled on a per-match base (which gives the term $1/m^I$). Similarly, the positive cross-side externality per-match is the sum across N^J participants of the increase in their match probability when another I-side user enters the platform:

$$N^J \frac{\partial m^J}{\partial N^I} \frac{1}{m^I} = \phi^I \tag{7}$$

The intuition of equations (6) and (7) is straightforward. Equation (6) shows that the matching elasticity is decreasing in the negative own-side externality. The reason for this is that an additional participant on side I decreases the matching probability for all I-side users. This effect is smaller if additional users are more easily matched, i.e. if the matching elasticity is larger. Similarly, equation (7) shows that the matching elasticity is increasing in the positive cross-side externality because an additional user on side I leads to an increase in the matching probability for J-side users that is higher the more efficient the platform is at matching I-side users.

3 Monopoly pricing

3.1 Platform profits

Assume that there is a private monopoly platform that sets per-match fees to both sides of the platform in a first stage. In the second stage potential users on both sides simultaneously decide to participate. In a third stage, matched users pay the per-match fee to the platform. In this setting, the monopoly matchmaker will choose per-match fees p^B and p^S to maximize profits given by:

$$\pi(p^B, p^S) = (p^B + p^S)M(N^B, N^S) \tag{8}$$

subject to equation (3). Also note that for simplicity there are assumed to be no costs for operating the platform.

3.2 Equilibrium prices

Proposition 1.1 follows from the first-order conditions of the profit maximization problem, in which $\mu^I \equiv (1 - F^I(\widetilde{v^I}))/f^I\,(\widetilde{v^I})$ is the inverse hazard rate of demand on side I and $\widetilde{v^I}$ is the net match valuation of the marginal I-side participant who is indifferent between participating or not such that $\widetilde{v^I} \equiv p^I$:[6]

Proposition 1.1 *At the optimal allocation, the per-match fee a private monopoly platform charges on each side $I = B, S$ $(J \neq I)$ is:*

$$p^I = \mu^I + \widetilde{v^I}(1 - \phi^I) - \widetilde{v^J}\phi^I \tag{9}$$

The first term on the right-hand side of equation (9) is the inverse hazard rate of demand, which is the classic Cournot (1838) measure of monopoly market power. The second term on the right-hand side shows how the platform internalizes the per-match negative own-side externality by taxing I-side users. This tax is larger when the matching elasticity is smaller, i.e. when the platform's matching technology is less efficient because the negative own-side externality is stronger. The final term on the right-hand side of equation (9) shows how the platform subsidizes the positive cross-side externality. This subsidy is increasing in the matching elasticity

[6] It is well-known from the platform pricing literature that in the described optimization problem, induced by the presence of network externalities, there is equilibrium multiplicity because of user coordination failures. Appendix 1.B discusses various approaches proposed by Caillaud and Jullien (2001, 2003) and Weyl (2010) of how the platform can uniquely establish its preferred equilibrium.

because a more efficient matching technology exists when an additional I-side user increases the matching probability of any J-side user by more.

In sum, it is shown that the platform's matching technology – characterized by negative own-side and positive cross-side externalities – can be meaningfully summarized by the matching elasticity and that the price a monopoly matchmaker charges on any side of the platform is decreasing in that side's matching elasticity.

3.3 Asymmetric pricing between sides of the platform

So far it was analyzed what determines the optimal price on a given side of the platform. An interesting question is what this implies for price asymmetries between sides of the platform. Using equation (9) and the fact that $\widetilde{v^I} \equiv p^I$ and $\widetilde{v^J} \equiv p^J$, it follows that:

$$p^B + p^S = \frac{\mu^B}{\phi^B} = \frac{\mu^S}{\phi^S} \text{ or that } \frac{\phi^B}{\phi^S} = \frac{\mu^B}{\mu^S} \tag{10}$$

where the inverse hazard rates are given by $\mu^I \equiv (1 - F^I(p^I))/f^I(p^I)$ for $I = B, S$. For example, assume that $\phi^B > \phi^S$ and that μ^I is decreasing in p^I for $I = B, S$. If the platform's technology is such that it is better at matching side-B than side-S users such that $\phi^B > \phi^S$, we must have that $\mu^B > \mu^S$. And if these inverse hazard rates are decreasing in their prices such that

$p^B < p^S$, the platform will charge a lower price to the side that has the highest matching elasticity.[7]

Whether μ^I is increasing or decreasing in p^I depends on the distribution of net match valuations.[8] To summarize these findings, assume for simplicity that net match valuations are symmetrically distributed and that the matching elasticities are constant. It can easily be shown that in this case the inverse hazard rate of the symmetric distribution must be decreasing for the second-order conditions of the model not to be violated (See Weyl (2010) for details), such that from proposition 1.1 and equation (10) it follows that:

Corollary 1.1 *For symmetrically distributed net match valuations ($F^B(.) = F^S(.)$) and a constant elasticity matching function (ϕ^B and ϕ^S constant), a monopoly platform always charges the lowest per-match fee to the side of the market with the highest matching elasticity:*

$$p^B < p^S \Leftrightarrow \phi^B > \phi^S \tag{11}$$

Note that corollary 1.1 assumes that matching elasticities are constant, i.e. independent of the chosen allocation by the platform. However,

[7] Also note that equation (10) is consistent with Rochet and Tirole (2003) who assume that each user on one side can interact with all the users on the other side. This implies a “matching elasticity” of unity on each side of the market. Consequently, they show that the optimal price structure satisfies $p^B + p^S = \mu^B = \mu^S$ or that price asymmetries can arise because of differences in underlying preferences between both sides of the platform. However, equation (10) shows that asymmetric prices can also be explained by the properties of the matching technology under which the platform operates even if preferences are symmetrically distributed.

[8] Fabinger and Weyl (2014) provide a formal discussion on the properties of demand and show that for the majority of distribution classes the inverse hazard rate is decreasing in price.

externalities induced by a marginal participant on either side might vary with the amount of users already present on both sides of the platform. For example, the externalities induced by an additional listing posted on an online listing platform for real estate could be very different whether that listing is the 10th or 1000th listing posted at the platform for a fixed amount of searching buyers. Chapter 2 of this dissertation provides a micro-foundation for the matching function to account for the specificities of the technology offered by a listing platform which allows for elasticities that vary with the allocation of buyers and sellers. The intuition of corollary 1.1 will remain valid even if the matching elasticities are no longer constants. Also then the side of the platform that has the higher matching elasticity is charged a lower price.

4 Socially optimal pricing and market distortions

4.1 The social planner's objective function

An important question is how the optimal pricing behavior of a private monopoly matchmaker discussed in the previous section compares to the outcome of a social planner. Assume a Pigouvian platform that sets prices to maximize its total social value, equal to the sum of aggregate utility of participants on the two sides of the market and the private platform's profits. The maximization problem for the welfare maximizer is then given by:

$$\max_{p_\omega^B, p_\omega^S} \omega = \left(\overline{v^B} + \overline{v^S}\right) M(N^B, N^S) \tag{12}$$

subject to equation (3) for $I = B, S$ and where:

$$\overline{v^I} \equiv \frac{1}{N^I} \int_{p^I}^{\infty} v^I f^I(v^I) dv^I \tag{13}$$

denotes the average net match valuation of participants on side $I = B, S$.

4.2 Pigouvian prices

Proposition 1.2 shows how the social maximizer internalizes the negative own-side and positive cross-side externality in the matching function:

Proposition 1.2 *At the optimal allocation, a Pigouvian platform charges a per-match fee p^I on each side $I = B, S$ ($J \neq I$) that equals:*

$$p_\omega^I = \overline{v^I}(1 - \phi^I) - \overline{v^J}\phi^I \tag{14}$$

From equation (14) it is clear that the Pigouvian platform also taxes the negative own-side and subsidizes the positive cross-side externality. However, it does so proportional to the average net match valuation of all users participating on the platform, and not the marginal user's match valuation as was the case in proposition 1.1. Before turning to the market distortions that result from these diverging incentives, first note that the Pigouvian price can also be written as:

$$p_\omega^I = \overline{v^I}\phi^J - \overline{v^J}\phi^I + \overline{v^I}(1 - \phi^I - \phi^J) \tag{15}$$

Equation (15) demonstrates that when the matching technology is characterized by constant returns to scale, the Pigouvian platform will unambiguously subsidize one side of the market and will exactly recover this subsidy from the other side. To see this, note that for $\phi^B + \phi^S = 1$, $p_\omega^B = \overline{v^B}\phi^S - \overline{v^S}\phi^B$ and $p_\omega^S = \overline{v^S}\phi^B - \overline{v^B}\phi^S$, which are exactly opposites:

$p_{\omega}^{B} = -p_{\omega}^{S}$. Which side of the market is subsidized depends on the matching technology, but also on the underlying heterogeneity of net match valuations. This result is further illustrated in the application in subsection 4.5.

4.3 Market Distortions

To illustrate the diverging incentives of the private and Pigouvian platform more clearly, equations (9) and (17) can be used to define the market distortion on side I as:

$$MD^{I} \equiv p^{I} - p_{\omega}^{I} = \mu^{I} + \underbrace{\left(\overline{v^{J}} - \widetilde{v^{J}}\right)\phi^{I} - \left(\overline{v^{I}} - \widetilde{v^{I}}\right)(1 - \phi^{I})}_{Spence\ distortion} \qquad (16)$$

The first term on the right-hand side of equation (19) is the inverse hazard rate of demand – the classic Cournot distortion – that captures the market power of the private monopolist. The final two terms on the right-hand side of equation (16) relate to the matching externalities and, following Weyl (2010), can be interpreted as a Spence distortion.[9]

The first term of the Spence distortion is consistent with Weyl (2010) who shows that the diverging incentives of the private and Pigouvian platform to account for positive cross-side externalities result in an upward distortion

[9] This terminology refers to the contribution of Spence (1975), who first pointed out that a monopoly that decides both on price (or quantity) and product quality tends to serve the quality preferences of marginal consumers instead of average consumers as would be optimal from a social point of view. Weyl (2010) revisits this argument for multi-sided platforms, by interpreting the amount of users on one side as a measure of quality of the platform service for users on the other side.

of prices.[10] By only internalizing the cross-side externality at the marginal and not average valuation of cross-side users, the private monopoly platform subsidizes this externality less than what is socially desirable. Consequently, the positive cross-side externality results in too high a price and too little participation. However, the last term in equation (16) shows that when the platform is a matchmaker, there also is a negative own-side externality that leads to a negative term in the Spence distortion. The reason for this is that the monopoly matchmaker taxes the negative own-side externality at the marginal less than average valuation of own-side users. This leads to a price that is less than what is socially desirable and too much participation.

Note that even though there is only one source of user heterogeneity in our setting, the Spence distortion can be downward if the negative own-side effect dominates the positive cross-side effect – a result that cannot be obtained from standard platform models where own-side congestion plays no role. On any side this is more likely to be the case if the matching elasticity is smaller, i.e. when the platform is a less efficient matchmaker on that side of the market. The next two subsections explore the relationship

[10] This result unambiguously holds when there is only one source of user heterogeneity in transaction valuations – or net match valuations in our setting – which implies $\overline{v^I} - \widetilde{v^I}$ is always positive. More generally, it is possible to have a negative Spence distortion also when there are only positive cross-side externalities. For example, Rochet and Tirole (2006) allow for multidimensional heterogeneity in user types and equilibrium in their model could result in a negative Spence distortion. As argued by Weyl (2010) this will be the case if the spread between the average transaction valuation of marginal and infra-marginal users is negative, which will depend on the dominating source of heterogeneity in user types.

between the platform's matching technology and market distortions on both sides of the market in greater detail.

4.4 Asymmetries in Spence distortions between sides of the platform

An interesting question is how the Spence distortion relates between sides of the platform and how this relationship depends on the platform's matching technology. To address this question, define $\overline{s^I} \equiv \overline{v^I} - p^I = \overline{v^I} - \widetilde{v^I}$ as the average per-match surplus of users on side $I = B, S$ of the market and note that (19) can be written as (with $J \neq I$):

$$MD^I = \mu^I + \overline{s^J}\phi^I - \overline{s^I}\phi^J - \overline{s^I}(1 - \phi^I - \phi^J) \tag{17}$$

For example, assume that the matching function has constant returns to scale, i.e. $\phi^B + \phi^S = 1$. If this is the case, the sign of the Spence distortion on side B coincides with the sign of $\overline{s^S}\phi^B - \overline{s^B}\phi^S$ and on side S with $\overline{s^B}\phi^S - \overline{s^S}\phi^B$. Consequently, when the Spence distortion is positive on one side, it must be negative on the other side. Equation (17) also provides a more general relationship between Spence distortions on both sides of the market and the platform's matching technology:

Corollary 1.2 *When the matching function has weakly decreasing returns to scale ($\phi^B + \phi^S \leq 1$), the Spence distortion is weakly negative on at least one side of the market. When the matching function has increasing returns to scale ($\phi^B + \phi^S > 1$), the Spence distortion is positive on at least one side of the market.*

Finally note that corollary 1.2 and equation (17) do not exclude the possibility that the market distortion as a whole is negative. For example, assume that the negative own-side externality on side S of the market is large such that ϕ^S is small and $\phi^B + \phi^S \leq 1$. From corollary 1.2 we then know that the Spence distortion must be negative on at least one side of the market. Say this is the high-price side S of the market. If on this side the negative Spence distortion is larger in absolute value than the classic distortion resulting from market power, equation (16) shows that the market distortion as a whole will be negative. What this means is that the private monopolist charges the high-price side S too low a price. Moreover, the Spence distortion on the low-price side B of the market will be too high, such that the inequality in market prices between both sides of the market is too low from a social point of view. The next subsection shows this is the case when heterogeneity is lognormally distributed assuming realistic parameter values and when there is a constant returns to scale matching function.

4.5 An application: lognormal heterogeneity and constant returns to scale matching

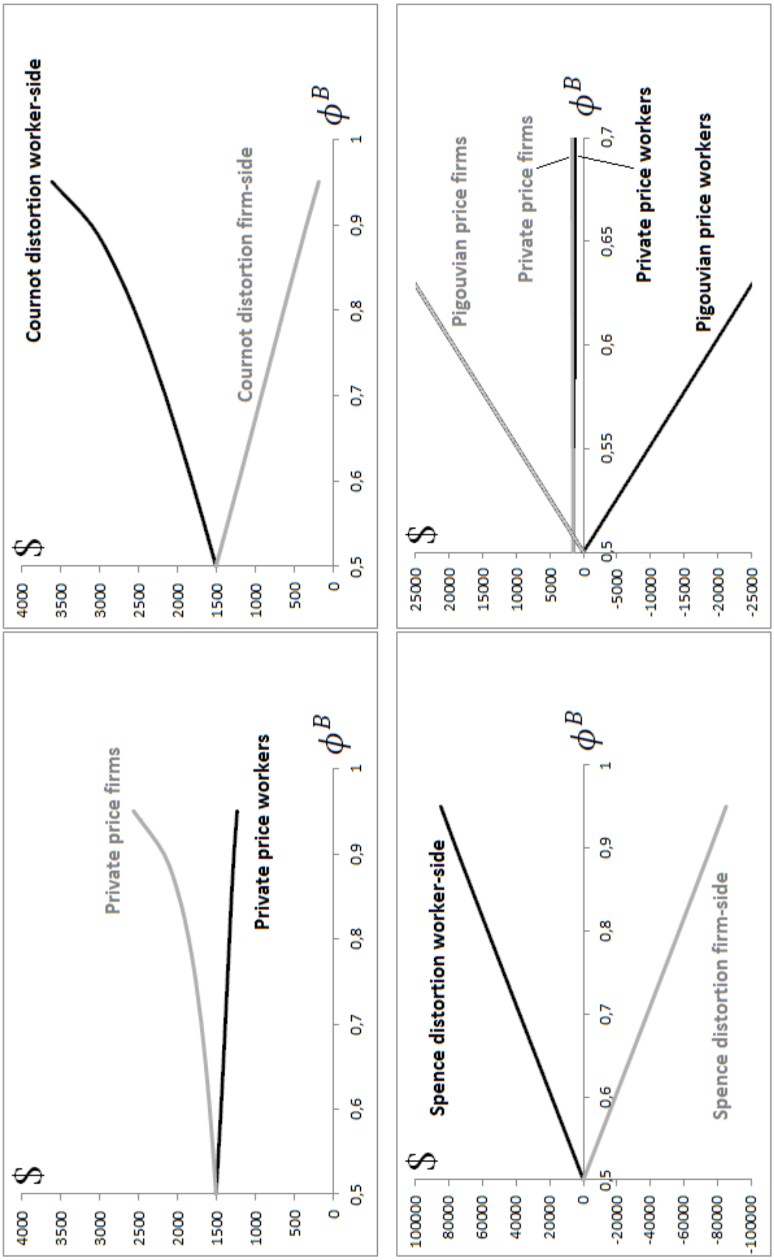
The previous subsection derived a relationship between the platform's matching technology and market distortions in a very general way. For example, it didn't determine on which side of the market the Spence distortion will be negative when the matching function has decreasing or constant returns to scale. And for the side that has the negative Spence distortion, whether the market distortion as a whole is also negative. To answer these type of questions one needs to be more specific about the underlying heterogeneity of user types and returns to scale in the matching function.

To illustrate this, think of side B as workers and of side S as firms in a labor market and assume lognormally distributed net match valuations, $F(.)$, for both workers and firms. This could be the case if labor productivity and therefore the wage is lognormally distributed, and firms value productivity and workers value wages. More specifically, assume that net match valuations are lognormally distributed on both sides with mean 10.4 and standard deviation 0.85. These parameter values are borrowed from Fabinger and Weyl (2014), who obtain these values by calibrating the lognormal distribution to the 2011 US yearly income distribution. Also assume a constant elasticity matching function homogeneous of degree 1 such that $\phi^B + \phi^S = 1$.

Remember from corollary 1.1 that if $\phi^B > \phi^S$ we must also have that $p^B < p^S$ when the inverse hazard rate of demand is decreasing in price, which can easily be shown to be the case in the present example. Moreover, from equation (20) it follows that the sign of the Spence distortion on the worker-side coincides with the sign of $\overline{s^S}\phi^B - \overline{s^B}\phi^S$ and on the firm-side with $\overline{s^B}\phi^S - \overline{s^S}\phi^B$. So if the Spence distortion is negative on one side of the market, it must be positive on the other. To see on which side it is positive and on which side it is negative, one needs to solve the model, which is done next.

Figure 1 illustrates the model's optimal prices and distortions on both sides of the market.

Figure 1: Optimal Prices and Distortions on Both Sides of the Market



The horizontal axes depict the matching elasticity on the worker-side ranging from 0.5 to 1, and hence the matching elasticity on the firm-side ranging from 0.5 to zero given that $\phi^B = 1 - \phi^S$. In other words, Figure 1 shows what happens to equilibrium prices and distortions on both sides of the market when the efficiency of the matching technology becomes more asymmetric in favor of the worker-side of the market.

The top-left panel of Figure 1 shows that the optimal private price for workers goes down and for firms goes up when ϕ^B increases, consistent with corollary 1.1. The top-right panel demonstrates that the classic Cournot distortion increases on the worker-side and decreases on the firm-side as ϕ^B increases, which is consistent with a decreasing inverse hazard rate. The bottom-left panel of Figure 1 shows that the Spence distortion is always positive for workers – i.e. the low-price side of the market, and always negative for firms – i.e. the high-price side of the market.

The market distortion as a whole on each side of the market is the sum of the Cournot and Spence distortions, given in the top-right and bottom-left panels of Figure 1 respectively. The total market distortion also is the difference between the private and Pigouvian prices, given in the bottom-right panel of Figure 1 for workers and for firms. Note that in this example the Pigouvian platform always subsidizes the more efficient worker-side of the market and recovers this subsidy from the firm-side, consistent with proposition 1.2 for a constant returns to scale matching function.

The bottom-right panel further implies that the total market distortion on the worker-side is unambiguously upward, even though the worker side is the low-priced side of the market. The private price for firms is smaller than their Pigouvian price for minimal asymmetry in the matching technology. In other words, despite that the firm-side is the high priced side of the market, the private price is still too low compared to what is socially optimal. Together with the positive total market distortion on the worker-side of the platform, this implies that the inequality in prices between sides of the platform is too low from a social point of view.

5 Conclusions

This chapter has shown how a private monopoly matchmaker internalizes the matching externalities – a negative own-side congestion and positive cross-side externality – that are inherent to its matching technology. If the matching technology is more efficient (i.e. the negative own-side externality is small and the positive cross-side externality is large) on a side of the market, the monopoly matchmaker will charge that side a lower price for its service.

In addition, the model also predicts that a monopoly matchmaker will only partially internalize the platform's matching externalities. In particular, the Spence distortion on a side of the market is increasing in the platform's matching efficiency for that side of the market. Comparing distortions between sides of the platform, it was also shown that the Spence distortion must be negative (positive) on at least one side of the market if the matching function exhibits decreasing or constant (increasing) returns to scale. For example, assuming that buyers are matched more efficiently in a constant returns to scale matching technology and that heterogeneity in user type is lognormally distributed using realistic parameter values, it was illustrated that prices are too high for buyers and too low for sellers for minimal asymmetries in matching elasticities between sides of the market. That is, inequality in market prices between sides of the online listing platform is too low from a social point of view.

Appendix 1.A: Participation fees, per-match fees and platform costs

All results in the main text are expressed in terms of fixed "per-match" fees denoted by p^I for side $I = B, S$. However, all results can instead be expressed in terms of fixed "participation fees" denoted by P^I, which is levied when users enter the platform, by simply substituting for $p^I = P^I/(M/N^I)$ in all expressions.

From the point of view of users, the indifference between paying a fixed per-match fee or a fixed participation fee directly follows from the assumptions of risk-neutrality, that matching is random (i.e. match probabilities are the same for users on a particular side) and that there are no transfers between matched users. To illustrate this, note that expected net utility of users when the platform can charge both types of fees is given by:

$$u^I = (v^I - p^I)m^I - P^I \qquad (A1)$$

Users participate when $v^I \geq \widetilde{v^I} \equiv P^I/m^I = p^I$ and demand is given by $N^I = 1 - F^I\left(\widetilde{v^I}\right)$. So, the platform can reach any desired allocation (N^B, N^S) whether one or both pricing instruments are available and is therefore indifferent between both.

That the platform is indifferent between fixed per-match and fixed participation fees only holds when platform costs are independent of the type of fee charged. To see this, assume that the platform incurs a per-match cost c proportional to the amount of matches that occur through the platform and a side-specific cost C^I to attract users on each side. When both fees are available to the platform, profits can be written as:

$$\pi = (p^B + p^S - c)M(N^B, N^S) + (P^B - C^B)N^B + (P^S - C^S)N^S \quad (A2)$$

When c, C^B and C^S are constants, the platform can maximize profits by choosing the optimal allocation N^B, N^S and by setting both types of fees such that the right amount of users on each side are attracted. Note that any allocation can be reached by setting $p^B = p^S = 0$ and adjusting the participation fee or by setting $P^B = P^S = 0$ and adjusting the per-match fee. But when c, C^B and C^S are not constant and depend on the value of the fees charged, the equivalence between the two fee types no longer holds. For example, if $c = 0$ when $p^B = p^S = 0$ and $c > 0$ when p^B or $p^S > 0$ and C^B and C^S constant, then the platform always prefers participation over flat fees. This scenario is particularly relevant when it is costly for matchmakers to observe individual matches in order to charge fixed per-match fees.[11]

Finally, note that the discussion so far assumed that the availability of a single pricing instrument on each side of the market suffices for the platform to reach its desired allocation. However, the presence of network externalities typically implies that the platform faces a problem of equilibrium multiplicity. As suggested by Caillaud and Jullien (2001), the availability of multiple pricing instruments on each side of the market can

[11] When the platform observes matches, it can typically do better than charging fixed per-match fees. When (part of) the match surplus is observed, the platform can price discriminate between users. For example, real estate brokers observe the selling price of a transaction or temporary help agencies observe the wage of the workers they assign to firms. These platforms typically price discriminate users by charging a commission fee proportional to the observed component of the match surplus. Analyzing proportional fee pricing is taken up in the third and fourth chapter of this dissertation.

help the platform to reach its preferred equilibrium. This issue is further addressed in Appendix 1.B.

Appendix 1.B: Equilibrium existence and uniqueness

It is well-known from the platform literature that if a platform chooses optimal prices in the first stage and users of the two sides simultaneously decide on participation in the second stage, there is an inherent problem of equilibrium multiplicity due to user coordination failures. Borrowing the terminology in Caillaud and Jullien (2001), a "bad-expectation" market allocation can always prevail in which case none of the users of either side participate, whatever prices charged by the platform. This because they have negative beliefs about the participation decision of users on the other side. So, the question is when the "good-expectation" market allocation will prevail that was described in the main text of the paper.

One way to address the issue is to assume a "rational-expectations" equilibrium as suggested by Caillaud and Jullien (2003). The intuition is that users on both sides have "favorable" beliefs about the participation decision of other users. When there exists an equilibrium that for users of both sides is favorable compared to, for example, the nonparticipation equilibrium, users will decide to participate. In our setting, when users on side B have favorable beliefs about the participation decision of S-side users, they participate when their net match valuation is greater than or equal to the per-match fee charged by the platform. So, demand on side B is equal to $N^B = 1 - F^B\ (p^B\ )$. Similarly, under favorable beliefs demand on side S is equal to $N^S = 1 - F^S(p^S\ )$ and there exists a unique set of prices that corresponds to the monopolist's profit maximizing allocation.

Moreover, as suggested by Caillaud and Jullien (2001), the assumption of favorable beliefs is unnecessary if the platform can use multiple pricing instruments. For example, when the platform can charge per-match as well as participation fees on each side of the market, it can grant a small participation subsidy arbitrarily close to zero such that all users on both sides are willing to participate. The platform can then adjust its per-match fees to establish its profit maximizing allocation. This would also be possible in the present model since the fixed per-match and participation fees are isomorphic as was discussed in Appendix 1.A.

In case the platform charges participation fees conditional on the amount of users or "insulating tariffs", Weyl (2010) shows how a unique equilibrium can exist. The intuition is that the platform can select any chosen amount of participants on a particular side by charging them a price conditional on the amount of users entering on the other side of the market. For this to be possible, there must be a unique price on a side of the market which can be written as a function of participation on both sides. In our model, inverse demand in terms of a fixed participation fee on side I of a market can be written as:

$$P^I(N^I, N^J) = F^{I^{-1}}(1 - N^I)\frac{M(N^I, N^J)}{N^I} \qquad (B1)$$

Now, note that for any given amount of J-side participants, say $\widetilde{N^J}$, there is a unique price that pins down or insulates the level of I-side participation desired by the platform, say $\widetilde{N^I}$, and $P^I\left(\widetilde{N^I}, \widetilde{N^J}\right)$ is the unique insulating tariff. Once the participation rate on side I is fixed there is no longer a coordination problem on side J and the platform can attract any desired amount of users. In other words, the platform can implement any desired allocation $\widetilde{N^B}, \widetilde{N^S}$ by charging an insulating tariff on at least one side of the market.

Chapter 2

Market distortions in online real estate advertisement pricing[1]

1 Introduction

This chapter aims to make two contributions. Firstly, to adjust the general platform matching model of the first chapter to the specific setting of a matchmaker that provides a listing service in a market for residential real estate. Secondly, to apply this model using data on the largest online real estate listing platform in Belgium with the purpose to learn about the efficiency of the matching technology and pricing behavior of the platform.

To do this, the analysis is built up as follows. Section 2 extends the model of chapter 1 to allow for Nash bargaining between matched buyers and sellers to divide the match surplus, such that the sales price of real estate properties is endogenously determined in the model. In addition, specific assumptions are imposed on the matching technology to account for the asymmetric nature of a matching process by which one side of the market lists advertisements (sellers) and the other side of the market uncoordinatedly searches through these advertisements (buyers). Optimal

[1] This chapter is single-authored and presents new material.

participation fees for buyers and listing fees for sellers are then derived for a monopolist and a Pigouvian planner.

The theoretical results show that the platforms, on top of the positive cross-side and negative own-side externalities that result from the matching process extensively discussed in chapter 1, account for an additional negative cross-side externality that results from the bargaining process. Attracting an additional buyer has a negative impact on the sales price sellers expect to receive because this buyer has a lower valuation for the good than the inframarginal buyers. Similarly, an additional seller has a higher reservation price of providing the good to the market than the inframarginal sellers, such that buyers expect to pay a higher price for the good when this sellers enters the platform. Notably, there are no diverging incentives between the monopoly and Pigouvian platform to account for this externality. This because all users on each side value this externality to the same extent and hence no additional Spencian distortion arises.

Section 3 describes the data and the institutional setting of the Belgian market for online real estate listings. Administrative data are available on total sales and average prices of real estate across districts in Belgium. In addition, a cross-section is available on the total amount of listings posted on the platform and on the listing fees charged to sellers. Finally, a large sample of listings is available with detailed characteristics and a proxy for time-to-sell - the online listing duration. The competitive environment of the platform is also described in this section with some supporting data on the size of the competitors. The observed platform clearly dominates the market. It is by far the largest in terms of visiting buyers and it seems to be the only platform that succeeds to charge a positive listing fee to sellers – the main competitors are all free of charge. This does not imply, however, that the platform can be treated as a monopolist. Should the platform exploit its dominant position through its fee setting, it would be likely to endanger its dominant position. Therefore, in the empirical analysis it is assumed that the platform serves full market demand on both sides of the market, but it is not assumed the observed listing fees are the fees a true monopolist would charge.

Section 4 presents the empirical analysis. Specific assumptions are imposed on the distributions of buyer and seller preference parameters and it is shown how the relevant distribution parameters can be linked to an observed distribution of sales prices. After some manipulation, the ask-price data from the listing sample is then used to back out the distribution parameters. In addition, from the estimated time-to-sell the relevant technology parameters and outcomes can also be derived from the data.

When all the model parameters are known, the counterfactual market outcomes of a Pigouvian planner and a monopolist can be calculated and compared to the observed market outcomes. The results suggest that the observed fees charged to buyers and sellers are *too low* compared to the socially optimal fees and hence that it would be welfare improving to attract less listings and searching buyers on the platform. This because the negative externalities that arise from the matching and bargaining process are not properly internalized. A true monopolist would charge even higher fees than the social planner on both sides of the market. Nevertheless, the results show that the monopoly outcome comes closer to the social optimum than the observed outcome. The results therefore suggest that (latent) competition is currently too strong in the Belgian market for real estate listings for the market to function efficiently.

In the literature, the related theoretical contributions are essentially the same as the ones described in chapter 1, so I will be brief on this. It should perhaps only be noted that the contribution of Niedermayer and Shneyerov (2013) is now more closely related than before, given that the present model also allows for transferable utility between matched participants. The results confirm Niedermayer and Shneyerov's result that, when abstracting from the matching externalities, the platform charges a higher fee to the side of the market with the larger bargaining weight.

This chapter relates to two strands of empirical literatures. On the one hand, there is a recent literature, among others, instigated by the work of Mark Rysman and Lapo Filistrucchi with their respective co-authors, that empirically investigates the nature of and efficiency issues in two-sided markets (see, for example, Rysman (2004, 2007), Argentesi and Filistrucchi (2007), Filistrucchi, Klein and Michielsen (2012), Gowrisankaran, Park and Rysman (2014), Jin and Rysman (2014)). This work mainly focusses on quantifying network externalities, estimating distortions from market power and evaluating the anti-trust implications of mergers between platforms (see also Evans and Noel (2008), Chandra and Collard-Wexler (2009) and Song (2013) on this) for various applications, like yellow pages, payment cards, newspapers, sports card conventions, DVD players, etc.

The present study deviates from this literature by topic, by studying a matching market and accounting for the additional externalities that arise in that setting, which are shown to be quantitatively more important than the familiar positive cross-side externalities and can reverse the conventional welfare effects of market power. The only empirical paper I am aware of with a similar research agenda is that of Loertscher and Niedermayer (2012), who investigate the efficiency of matching intermediaries that use percentage fees as a pricing instrument and apply their model to the Boston real estate brokerage market in the 1990s. They focus on direct mechanisms to model the matching and bargaining process, however, and abstract from the externalities that are the emphasis of the present analysis.

On the other hand, there is a recent literature that evaluates the efficiency of matching technologies in real estate markets. Genesove and Han (2012) explicitly estimate the matching function across MSA's in the US for real estate markets as a whole. They do not distinguish between matching channels, however, and hence do not link their estimates to the behavior of private matching platforms active in the market. In addition, Hendel, Nevo and Ortalo-Magné (2009) compare the efficiency of two types of matching platforms in the US, one operated by real estate brokers (MLS) and one that services independent sellers (FSBO), and investigate whether selling one's own property at a low listing fee is worth the effort compared to using a more expensive broker (also see Bernheim and Meer (2010) and Levitt and Syverson (2008)). They do not investigate, however, whether the listing fee by itself is set efficiently. Another crucial difference with the present setting is that in Belgium independent sellers and brokers do not list their properties on separate platforms and the analysis makes no distinction between these two user groups when evaluating the matching efficiency of the platform.

2 A model of online real estate advertisement pricing

2.1 User preferences and demand

Consider a mass S of sellers who contemplate posting $\gamma \geq 1$ advertisements on an online listing platform with the purpose to sell a single homogeneous real estate property. In return for this sellers are charged a flat fee P^S for each listing. Sellers might post their advertisement more than once, for example, to get more exposure on the platform. Similarly, there is a mass B of buyers that potentially use the platform in their search for a real estate property. Buyers are charged a participation fee P^B to use the technology offered by the platform to search through the database of listings, independently of how intensively they use the technology. Denote the search intensity of buyers by $\alpha \geq 0$. The listing and search intensities are considered exogenous and are assumed to be same across all sellers and buyers, respectively. Depending on the fees charged by the platform, N^S sellers and N^B buyers participate. In turn, depending on N^S and N^B and the matching technology offered by the platform, sellers have a probability m^S and buyers a probability m^B of being matched. These match probabilities are assumed to be the same for all participants on the same side, but allowed to differ across sides of the market. The specificities of the matching technology offered by the platform are further described in the next subsection.

Sellers are heterogeneous in their reservation price of providing the real estate property to the market through the platform, denoted by s, assumed to be smoothly distributed by $F^S(.)$ on $[s^L, s^H]$ with density $f^S(.)$.

Similarly, buyers are heterogeneous in their valuation for the homogeneous real estate property, denoted by b, distributed by $F^B(.)$ on $[b^L, b^H]$ with density $f^B(.)$. When a seller type s and a buyer type b are matched, the match surplus is efficiently divided between the two parties, assuming that the participation fees charged at entry are sunk when the match is established. That is, the fees are not taken up in the bargain over the sales price of the property. More specifically, assume that the sales price ρ is chosen to maximize the following Nash bargain:

$$\max_{\rho}(b-\rho)^{1-\beta}\,(\rho-s)^{\beta} \qquad (1)$$

where β denotes the bargaining weight of sellers and hence $1-\beta$ is the bargaining weight of buyers.[2] This results in the following expression for the sales price:

$$\rho(b,s)=\beta b+(1-\beta)s \qquad (2)$$

In the described setting, expected utility of sellers when listing their real estate property at the platform is equal to:

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[2] The assumptions on the bargaining process have two convenient implications for the purpose of the present analysis. On the one hand, Nash bargaining is efficient in the sense that any match for which the buyer valuation is sufficiently high to cover the seller reservation price will be established. In alternative price determination games there might be additional distortions that arise from seller and/or buyer market power or informational imperfections. Given the focus of the present analysis on the distortions that possibly arise the private behavior of the listing platform, however, I prefer to exclude any additional potential inefficiencies. On the other hand, by assuming that sales prices are determined at the individual transaction level, rather than through a competitive market clearing mechanism (which would also exclude the aforementioned additional distortions), implies *ex post* sales price dispersion for homogeneous real estate goods. In the empirical part of this chapter, it is precisely the residual variation in sales prices (after controlling for observable real estate characteristics) that will be used to identify the buyer demand and seller supply parameters of the model.

$$u^S = \big(\rho(\bar{b}, s) - s\big)m^S - \gamma P^S \tag{3}$$

where $\bar{b}$ denotes the expected buyer type, or the average buyer valuation, defined as:

$$\bar{b} \equiv \frac{1}{1 - F^B(\tilde{b})} \int_{\tilde{b}}^{b^H} b f^B(b) db \tag{4}$$

in which $\tilde{b}$ denotes the valuation of the marginal buyer that participates at the platform.

Similarly, expected utility of buyers to search for a real estate property on the listing platform is equal to:

$$u^B = \big(b - \rho(b, \bar{s})\big)m^B - P^B \tag{5}$$

where $\bar{s}$ denotes the expected or average seller reservation price, defined as:

$$\bar{s} \equiv \frac{1}{F^S(\tilde{s})} \int_{s^L}^{\tilde{s}} s f^S(s) ds \tag{6}$$

in which $\tilde{s}$ denotes the reservation price of the marginal seller that participates at the platform.

Sellers participate when $u^S \geq 0$, such that the marginal seller reservation price is equal to:

$$\tilde{s} = \bar{b} - \frac{1}{\beta} p^S \tag{7}$$

where $p^S = \gamma P^S / m^S$ denotes the expected per-match fee for sellers. Given that the fee charged by the platform is not taken up in the bargain over the sales price, the same equivalence holds between p^S and P^S as described in the first chapter. Seller demand for the platform service follows:

$$N^S = SF^S(\tilde{s}) \tag{8}$$

Inverse seller demand can hence be written as:

$$\begin{aligned} p^S &= \beta\left(\bar{b} - F^{S^{-1}}(N^S/S)\right) \\ &= \beta\left(\bar{b} - \tilde{s}\right) \end{aligned} \tag{9}$$

Similarly, buyers participate when $u^B \geq 0$, such that the marginal buyer valuation can be written as:

$$\tilde{b} = \bar{s} + \frac{1}{1-\beta} p^B \tag{10}$$

where $p^B = P^B/m^B$ denotes the expected per-match fee for buyers. Buyer demand is equal to:

$$N^B = B\left(1 - F^B\left(\tilde{b}\right)\right) \tag{11}$$

Inverse buyer demand again follows:

$$\begin{aligned} p^B &= (1-\beta)\left(F^{B^{-1}}(1-(N^B/B)\,) - \bar{s}\right) \\ &= (1-\beta)\left(\tilde{b} - \bar{s}\right) \end{aligned} \tag{12}$$

Note that even though there is an additional externality that affects user preferences compared to the model described in chapter 1 – utility is now affected by cross-side participation not only through the match probability, but also through the expected sales price – the coordination problem faced by the platform is essentially the same: the participation decision of users on one side of the market depends on their expectation about participation of the users on the other side of the market. As discussed in appendix 1.B of chapter 1, the platform can resolve this problem by charging *insulating tariffs,* as suggested by Weyl (2010). That is, for any number of buyers that show up at the platform, the participation fee of sellers can be adjusted to attract the desired number of sellers and vice versa. To see this, note from expression (9) that inverse seller demand solely depends on N^S (through $\tilde{s} = F^{S^{-1}}(N^S/S)$) and N^B (through $\bar{b}$ in which $\tilde{b} = F^{B^{-1}}(1-(N^B/B)\,)$) and hence is independent of p^B. Similarly, inverse buyer demand, given by expression (12), depends only on N^B and N^S and is independent of p^S. Hence, any desired allocation N^S, N^B can be established by properly adjusting p^S and p^B.

2.2 Platform matching technology

Assume the match probability of sellers and buyers, respectively, is given by:

$$m^S = \frac{M}{N^S} \text{ and } m^B = \frac{M}{N^B} \tag{13}$$

in which the matching function $M = M(N^B, N^S)$ denotes the number of matches that occur through the platform given that N^B buyers and N^S sellers participate. The matching elasticity for sellers and buyers, respectively, is defined as:

$$\phi^S \equiv \frac{\partial M}{\partial N^S}\frac{N^S}{M} \text{ and } \phi^B \equiv \frac{\partial M}{\partial N^B}\frac{N^B}{M} \tag{14}$$

As in chapter 1, ϕ^S is interpreted as a measure for the positive cross-side externalities exerted by sellers on the buyer-side and $1 - \phi^S$ measures (the absolute value of) own-side congestion among sellers. Similarly, ϕ^B measures the positive cross-side externalities induced by the participation decision of buyers and $1 - \phi^B$ is a measure of congestion among buyers.

Rather than assuming a general matching function as in the previous chapter, this chapter imposes specific assumptions on the matching process to account for the specificities of a matchmaker that provides an online listing service. More specifically, a familiar microfoundation of the matching function – "urn-ball" matching – is reinterpreted in the context of online listings. Petrongolo and Pissarides (2001) provide a detailed discussion on the origin and applications of the urn-ball matching function.

Assume that sellers participate by posting advertisements for their real estate property on the platform and that buyers uncoordinatedly search through these listings. More specifically, each participating seller lists γ advertisements and each participating buyer randomly applies to α advertisements. So, some sellers may receive no applications while others may receive many. It is assumed that those sellers receiving more applications randomly select one buyer, such that some buyers that applied will remain unmatched. In this setting, it is the presence of coordination failures among buyers that characterizes the platform's matching technology and externalities.

To fully capture the intuition of this matching process it is convenient to build up the matching function step by step. Given that N^S sellers list γ

advertisements on the platform and that each of the N^B buyers randomly applies to α advertisements, each seller has a probability $\gamma/\gamma N^S$ of receiving an application from any given buyer, assuming a buyer applies at most once to a particular seller. Hence, the probability of not receiving an application from that buyer is $(1 - 1/N^S)$. In total, αN^B applications get sent out, so the probability that a seller ends up without any buyer is then given by:

$$(1 - 1/N^S)^{\alpha N^B} \approx \exp(-\alpha N^B/N^S\,) \tag{15}$$

where the approximation holds only if N^S is sufficiently large. Hence, the probability that a given seller will be matched to a buyer is approximated by $1 - \exp(-(\alpha N^B)/N^S)$ and the expected number of total matches is then given by the following matching function:

$$M(N^B, N^S) = N^S(1 - \exp(-\alpha N^B/N^S)) \tag{16}$$

It follows from this matching function that the matching elasticities with respect to buyers and sellers are, respectively:

$$\phi^B = \frac{N^B}{N^S}\frac{\exp(-\alpha N^B/N^S)}{(1 - \exp(-\alpha N^B/N^S))} \text{ and } \phi^S = 1 - \phi^B \tag{17}$$

Expression (17) illustrates that the matching function is homogeneous of degree 1 and that the matching elasticities are not constant, but rather depend on the allocation of buyers and sellers. Moreover, the matching elasticities are not symmetric between both sides of the platform. For example, assuming that $N^S = N^B$ and that $\alpha = 1$, it follows that $\phi^S = 0.42$ and $\phi^B = 0.58$. The higher matching elasticity for buyers than for sellers captures the fact that the listing platform is more efficient at matching buyers than sellers. One intuition for this is that buyers are “active” in this model in the sense that they apply to advertisements taking into account the (expected) behavior of other buyers. In contrast, sellers are “passive” in the sense that they simply post listings and hope that at least one buyer responds.

Note that the parameter α can be interpreted more broadly as simply being the number of applications sent out by each buyer. For example, if the static matching game described here is repeated many times and when every period a fraction $1-\alpha$ of buyers does not apply to any advertisement and the remaining fraction α applies to a single listing, the per-period matching function will also exactly be expression (16). However, the parameter α will now be between 0 and 1 rather than being larger than or equal to unity. Even more loosely, given that M is increasing in α, in the presence of other frictions on top the coordination frictions described here, one can also think of this parameter as generally capturing the efficiency of the matching technology offered by the platform in terms of resolving these frictions. For example, housing is an extremely heterogeneous good and not every buyer can be matched to any seller. A higher α then implies that the platform technology is better at bringing the right buyer to the right seller.

In addition, note that the matching function is independent of γ, the amount of listings posted by each seller. This because all sellers have the same listing intensity and hence the same probability of receiving an application from each buyer. The seller listing intensity do will play an important role to properly identify the unique amount sellers at platform in the empirical part of this paper.

2.3 Platform profits and social value

A monopoly platform maximizes profits:

$$\pi = (p^A + p^B)M(N^A, N^B) \tag{18}$$

by choosing the optimal allocation of buyers and sellers, subject to inverse buyer and seller demand, given by expressions (9) and (12).

Total social value, equal to the sum of aggregate utility of participants on the two sides of the market and the private platform's profits, can be written as:

$$\omega = \left(\bar{b} - \bar{s}\right)M(N^A, N^B) \tag{19}$$

A Pigouvian planner optimally chooses the allocation of buyers and sellers by maximizing (19), subject to (9) and (12).

Note that the platform is assumed to incur no costs. It seems reasonable to assume that the marginal costs to attract sellers and buyers are approximately zero for a listing platform. Sellers themselves fill in the details of their listings and they simply pay the listing fee once they are ready to upload. Similarly, buyers use the technology of the platform as a tool to search for a suited property, so they also incur their search costs themselves. The platform only needs to assure that the technology runs properly, which might entail some fixed operating costs, but no marginal costs. Fixed costs should not influence the short-run pricing decision of the platform and are therefore ignored in the remainder of the analysis.

2.4 Results

Proposition 2.1 follows from the first-order conditions of the profit maximization problem, in which $\mu^B \equiv (1 - F^B(\tilde{b}))/f^B(\tilde{b})$ is the inverse hazard rate of demand for buyers and $\mu^S = F^S(\tilde{s})/f^S(\tilde{s})$ is the inverse hazard rate of demand for sellers. Equivalently to chapter 1, $\widetilde{v^B}$ denotes the net expected match value of the marginal buyer that participates and $\widetilde{v^S}$ denotes the net expected match value of the marginal seller. In the present setting these are equal to:

$$\widetilde{v^B} = (1-\beta)\left(\tilde{b} - \bar{s}\right) \text{ and } \widetilde{v^S} = \beta\left(\bar{b} - \tilde{s}\right) \tag{20}$$

The marginal participants are indifferent between participating or not such that $\widetilde{v^B} = p^B$ and $\widetilde{v^S} = p^S$.

Proposition 2.1 *At the optimal allocation, the per-match fee a private monopoly platform charges to buyers and sellers, respectively, is:*

$$p^B = (1-\beta)\mu^B + \widetilde{v^B}(1-\phi^B) - \widetilde{v^S}\phi^B + \beta\left(\bar{b} - \tilde{b}\right) \tag{21}$$

$$p^S = \beta\mu^S + \widetilde{v^S}(1-\phi^S) - \widetilde{v^B}\phi^S + (1-\beta)(\tilde{s} - \bar{s}) \tag{22}$$

Comparing the results in proposition 2.1 to those in proposition 1.1 in chapter 1 nicely illustrates the implications of allowing matched participants to bargain over the division of the match surplus on the optimal pricing behavior of a monopoly platform. Remember that β and $1-\beta$ denote the bargaining weight of sellers and buyers, respectively. Expressions (21) and (22) demonstrate that the inverse hazard rates on each side are now weighted by the bargaining weight of participants on that side.

So, all else equal, the platform possesses more market power on the side with stronger bargaining weight. This seems intuitive, given that a larger bargaining weight results in a higher willingness-to-pay for the platform service. The intuition of the second and third term in expressions (21) and (22) is the same as in proposition 1.1. The platform taxes the negative congestion effect and subsidizes the positive indirect network effect that results from the random matching process to the extent that the marginal participant on each side is willing to pay for this.

The last term in expressions (21) and (22) is novel and it captures how the monopolist accounts for the additional externality that arises in the presence of bargaining. When an additional buyer enters the platform, this will have a negative impact on the expected sales price of sellers, given that a marginal buyer always has a lower willingness-to-pay for the good than inframarginal buyers. To see this, remember that the sales price any seller type s expects to receive is equal to $\rho(\bar{b}, s) = \beta\bar{b} + (1-\beta)s$. So, the impact on the expected sales price of an additional buyer entering the platform is $-\beta(\bar{b} - \tilde{b})/N^B$. Adding up this effect for all buyers that enter the platform, the magnitude of this negative externality is exactly the tax the platform imposes on buyers in the optimal price charged to buyers: $\beta(\bar{b} - \tilde{b})$. Similarly, an additional seller entering the platform has a positive effect on the sales price buyers expect to pay and hence a negative effect on expected buyer utility. This because the marginal seller has a higher reservation price of providing the good to the market and will only settle for a higher sales price relative to the inframarginal sellers. The sales price any buyer type b expects to pay is $\rho(b, \bar{s}) = \beta b + (1-\beta)\bar{s}$ and the impact of an additional seller on this is $(1-\beta)(\tilde{s}-\bar{s})/N^s$. Adding this up over all sellers that participate is again exactly the tax imposed on sellers in the optimal seller fee: $(1-\beta)(\tilde{s}-\bar{s})$.

Proposition 2.2 shows how the social planner sets the per-match fee to maximize total social value, in which $\overline{v^B}$ denotes the net expected match value of the average buyer that participates and $\overline{v^S}$ denotes the net expected match value of the average seller:

$$\overline{v^B} = (1-\beta)\left(\bar{b}-\bar{s}\right) \text{ and } \overline{v^S} = \beta\left(\bar{b}-\bar{s}\right) \tag{23}$$

Proposition 2.2 *At the optimal allocation, the per-match fee a Pigouvian platform charges to buyers and sellers, respectively, is:*

$$p_\omega^B = \overline{v^B}(1-\phi^B) - \overline{v^S}\phi^B + \beta\left(\bar{b}-\tilde{b}\right) \tag{24}$$

$$p_\omega^S = \overline{v^S}(1-\phi^S) - \overline{v^B}\phi^S + (1-\beta)(\tilde{s}-\bar{s}) \tag{25}$$

The first two terms in expressions (24) and (25) demonstrate that the social planner taxes the negative congestion effect and subsidizes the positive indirect network effect to the extent that the average participant on each side is willing to pay for this, rather than the marginal participant as the private monopoly does, resulting in a similar Spence distortion as described in chapter 1. The last terms, however, show that the Pigouvian platform internalizes the negative cross-side externality that affects the expected cross-side sales price exactly the same way as the monopolist does. The reason for this is that every buyer type b and every seller type s value this externality to the same extent, so no additional Spencian distortion arises here.

The remainder of this chapter aims to quantify and compare private and socially optimal fees charged to buyers and sellers using preference and matching parameters derived from data from a large online real estate listing platform in Belgium. Before showing the results, the following section first describes the data and institutional setting of the investigated online real estate advertisements market.

3 Data and institutional setting of the Belgian online real estate advertisements market

Belgium is a small country in Western Europe with a surface of approximately 30500 sq.km. and the population counts about 11.1 million citizens. The country consists of three main regions (the bilingual Brussels Capital Region, the northern Dutch-speaking Flemish region and the southern French-speaking Walloon region) and is further subdivided into 10 provinces, 43 districts (cities including their respective agglomerations and rural areas), 589 municipalities (most disaggregated level of political relevance, each municipality has a local government and elected major) and 1146 zip-codes (towns in rural areas and local residential areas in urban parts of the country).

3.1 Administrative data on the number of residential real estate sales and average sales prices by district

The first dataset used in the empirical analysis is publicly available data from the national statistics office Belgium on total sales and average prices of real estate at the level of districts on quarterly basis from 1990Q1 to 2013Q4. The data categorizes real estate into "ordinary residential houses", “villas, bungalows and manors”, “apartments” and “residential land”. Throughout the analysis only the distinction between “houses” and “apartments” is made. Sales of houses by district is calculated as the sum of ordinary residential houses and villas, bungalows and manors. The average price of houses is calculated as the weighted average by sales of these two categories. The data on residential land is not used. Table 1 reports summary statistics on total sales and average prices in 2013.

Table 1: total sales and average prices of houses and apartments in 2013

Variable	Obs	Mean	Std. Dev.	Min	Max	Total
sales houses	43	1847	1496	309	7303	79416
sales apartments	43	985	1747	27	9170	42367
average price houses (€)	43	206739	57795	127246	399754	206739
average price apartments (€)	43	185096	38450	119175	315215	185096

The table shows that on average 1847 houses were sold across districts in 2013, ranging from 309 in Bastogne to 7303 in the district of Antwerp, and the average number of apartments sold was 985, ranging from 27 in Philippeville to 9170 in the Brussels Capital Region. In total, 79416 houses and 42367 apartments were sold in 2013 across the country. The average price of housing is about €206000, with a minimum of €127000 in Charleroi and a maximum of €400000 in the Brussels Capital Region. Apartments sell on average for €185000, going from €120000 in Thuin to €315000 in the district of Bruges.

3.2 Platform data on the number of listings by zip-code

The second dataset used is a cross-section of listings posted on the largest online listing platform for real estate in Belgium in early April 2014. Within each zip-code, the data contains a variable with the total number of houses that were listed on the platform at the time the data were collected and one with the number of houses labeled as “new construction”. For both of these categories, there is an additional variable that reports the number of “recent listings” that were posted on the platform at most 15 days before the time of collection. The same four variables are available for apartments.

The sales data reported in table 1 above come from the national land registry office and only contain “old constructions”, in the sense that “new constructions” that are sold for the first time do not have to be reported in Belgium by law and therefore are not counted in the number of sales by district. To make the listings data comparable to the sales data, the “new construction” listings are therefore extracted from the total amount of listings to get a proxy for the number of “old construction” listings, which is the measure used for the subsequent analysis. Table 2 reports summary statistics for the adjusted number of total (all) and recent (max 15 days) listings for houses and apartments, aggregated up to the level of districts.

Table 2: cross-section of total and recent listings on the platform

Variable	Obs	Mean	Std. Dev.	Min	Max	Total
listings houses (all)	43	1328	1045	290	5366	57098
listings apartments (all)	43	898	1536	14	8513	38626
listings houses (max 15 days)	43	200	169	34	806	8611
listings apartments (max 15 days)	43	84	192	0	1048	3621

Table 2 illustrates that the average number of total listings for houses and apartments across districts is 1328 and 898, respectively. The average number of recent listings for houses and apartments is 200 and 84, respectively. There is again significant variation across districts and as expected this variation is closely related to the number of sales across districts reported in table 1. The correlation coefficient between housing sales and total housing listings across districts is 0.95 and between total housing sales and recent housing listings 0.94. Similarly, for apartments the correlation coefficients are 0.98 and 0.98, respectively. In total, 57098 houses and 38626 apartments were listed on the platform for Belgium as a whole at the time the data was collected. In addition, a total of 8611 recent housing listings and 3621 recent apartment listings were posted on the platform at that time.

3.3 Sample of listings with detailed characteristics

The third dataset used is a sample of 7149 listings posted on the platform early December 2013. All the listings were recent listings at the time, i.e. they were online at most 15 days when the data was collected. Subsequently, the status of all the listings (online vs. offline) was checked on weekly basis for 20 weeks. Table 3 reports a brief description of the available listing characteristics and their summary statistics. On top of the reported variables, the location of each listed property is also available at the level of zip-codes.

Table 3: sample listings with characteristics

Variable	Description	Obs	Mean	St. Dev.
category	= 1 if house, = 0 if apartment	7149	0.72	0.45
agency	= 1 if the seller is a real estate agency, = 0 otherwise	7149	0.75	0.43
notary	= 1 if the seller is a notary, = 0 otherwise	7149	0.09	0.29
owner	= 1 if the seller is an independent owner, = 0 otherwise	7149	0.16	0.37
askprice	ask-price in euros at time of placement listing	6846	307237	337215
size	living surface of property in sq. m.	4967	171	109
bedrooms	number of bedrooms	6993	2.98	1.23
weeks online	number of weeks a listing was online	7149	14.30	6.61
offline	= 1 if listing offline after 21 weeks, = 0 if still online	7149	0.66	0.48

Table 3 shows that 72% of the listings in the sample are houses and 28% apartments. In addition, 75% was listed by a real estate agency, 9% by a notary and 16% by independent sellers (for-sale-by-owner). The average ask-price for properties is about €300000 which is about €100000 more than the price at which properties are actually sold as suggested by table 1 above. The average living surface of properties in squared meters is 171, with an average of 3 bedrooms. Note that the ask-price, size and number of bedrooms is not available for all the listings. Sellers might both deliberately or accidentally have withheld this information when posting the property on the platform. The average time online was 14.3 weeks. However, this is an underestimate of the true average time online given that the observed online durations are right censored at 21 weeks (assuming that each listing was online 1 week at the start of the observation period). The final row in the table shows that 66% of the listing was offline after 21 weeks, but the remaining 34% was still online.

A few notes are in place here about the institutional setting of the Belgian market for real estate compared to, for example, the US market. Firstly, there is the role of notaries. A notary is a publicly appointed legal administrator who, among other things, is assigned to legally close real estate transactions among sellers and buyers. Furthermore, every real estate transaction has to be registered by a notary by law. On top of this, notaries might also take up the role sellers of real estate. For example, in the case of seizures due to failed mortgages, notaries are typically appointed to sell the property on behalf of the bank, which usually happens through a public auction. Or, notaries might also sell real estate on behalf of sellers who request this, in which case they essentially take up the role of a real estate agent. Table 1 shows that 9% of the listings in the sample are placed by notaries.

Secondly, buyers are almost never represented by a real estate agent in Belgium. This in contrast to the US, for example, where buyers are almost always represented by a broker. This can again be explained by the presence of notaries. As mentioned, notaries assure that every real estate transaction is properly closed by all legal requirements, so there is little incentive for buyers to hire an additional intermediary to take up this role. Instead, buyers independently search for real estate properties of their interest, usually through online listing platforms, like the one described here. Once a buyer has taken interest in a property, three scenarios can occur. Firstly, the property is put up for sale by an independent seller, in which case the buyer directly contacts the seller. The buyer can visit the property and possibly make an offer. If the buyer and the seller come to an agreement, they go to a notary to legally close the transaction. Secondly, if the seller hired a real estate agent, the buyer deals with the agent to visit the property and bargain over the price. If they come to an agreement and the seller also consents, all three parties visit a notary to close the transaction. Finally, when a property is offered by a notary, the buyer can either visit the public auction at a fixed date or the notary takes up the role of a real estate agent on behalf of a seller. Especially in the latter case, but also in the former two scenarios, a buyer always can employ a notary of his or her choosing if the buyer feels that the notary hired by the seller might underrepresent his or her interests. In this case the transaction is closed by both notaries, similar to the US where buyers and sellers usually each hire a broker.

3.4 Platform listing fees

Table 4 reports the publicly available listing fees charged to sellers for placing a real estate advertisement at the online platform.

Table 4: listing fees

Properties with an ask price below € 125000		
1 month	€ 44.9	
2 months	€ 54.9	
Properties with an ask price above € 125000		
1 month	€ 54.9	
2 months	€ 64.9	
3 months	€ 74.9	"recommended minimum duration"
4 months	€ 84.8	"recommended duration"
6 months	€ 99.0	"most advantageous"
12 months	€ 149.0	
Option PLUS	€ 44.9	"additional visibility for total duration"
	€ 24.9	"additional visibility for 1 month"

The table shows that sellers can freely choose their listing duration, ranging from one month to 12 months and the per-month fee is regressive in the listing duration. Listings posted with an ask-price below €125000 get a discount, at least for the first two months. Seller can also choose a "plus" option, in which case the advertisement receives additional visibility for the entire or part of the listing duration. Listings with this option get highlighted and are shown at the top of the search page when the relevant search criteria are entered.

Unfortunately, for the listings in the sample described in table 3, the tariff sellers chose to list their property is not available. In what follows, it will be assumed a representative seller chooses the recommended duration of 4 months, which corresponds to a weekly listing fee of €4.8. Also note that buyers are never charged to use the platform service in any way. They can freely use the technology offered by the platform to search through the database of real estate properties under general or very specific search criteria of their choosing.

3.5 Competitive environment of the platform

The model described in section 2 assumes a monopoly platform. The platform under observation, however, although it is by far the largest in terms daily visits, is not the only online real estate listing platform active in the Belgian market. There are two other noteworthy “general” real estate listing platforms that offer a similar service than the platform for which the data are available. In addition, there are some “specialized” platforms that either focus on a particular type of listings, like luxurious real estate, or focus on real estate that is sold in a particular region. Unfortunately, I have no detailed listing data available for these competitors. However, by manual inspection of the online market structure, I am confident that the following description of the nature of platform competition fits the market under investigation well.[3]

On the buyer-side, all the competitors allow for free buyer participation. According to CIM (Centre for Media Information), the weekly visits attracted by the platform under investigation is about 5 times the number attracted by its largest competitor and about 6 times that of the second

[3] See De Smet and Van Cayseele (2010) for a more detailed description of the Belgian market for real estate listings.

largest competitor.[4] So, it seems reasonable to assume that a representative buyer first will visit the platform under observation and perhaps in second instance will also visit the other webpages to make sure to be fully informed about all market offers.

On the seller-side, most competitors offer free listings (except for some of the specialized platforms) and it seems like these platforms make their revenues by attracting other types of product advertisers which are displayed at the platform webpages. Consequently, the second largest competitor attracts about the same amount of listings as the observed platform and the second largest competitor attracts about two thirds of this amount, as reported on their webpages. It therefore seems reasonable to assume that any seller who is willing to pay the fee described in table 4 above will do so because this platform has the largest base of potential buyers. Most of them will also post their listing on the free platforms to make sure to get full exposure. In addition, there might be some sellers who are not willing to pay the fee and will only post their listing on the free platforms.

In what follows, it will be assumed that the platform under observation serves full market demand on both the buyer- and seller-side of the market. However, it will *not* be assumed that the observed fees charged by the

[4] CIM reported for the first week of May 2014 that the platform under observation attracted 240156 "sessions" of visiting buyers. A session starts when a person visits the platform, during the session the person searches through the advertisements and the session ends when the person leaves the website. One should not think of this number as "unique" buyers visiting the platform in a week. If a buyer is searching intensively for real estate he or she is expected to visit the platform multiple times a week, or even multiple times a day. For the largest competitor 49548 sessions were reported and for the second largest competitor 39498.

platform are necessarily the fees a true monopolist would charge. That is, the fees that would be charged when the only outside option to buyers and sellers would be simply not to purchase or sell their properties, because there is no other way to find a trading partner besides using this particular platform.

Without explicitly modeling them here, some foundations for the observed market structure can be found in two-sided markets literature. To start, it is well-known from this literature that when participants “multi-home” (use multiple platforms) on one or both sides of the market this tends to tends to reduce market power compared to the case where competitors can exclusively isolate participants on one or both sides of the market (e.g. Rochet and Tirole (2003), Armstrong and Wright (2007) and White and Weyl (2012)). In the market investigated here, participants on both sides multi-home which might explain, despite the fact that one platform clearly dominates the market, that market power is limited.

In addition, De Smet and Van Cayseele (2010) investigate a platform business model referred to as “spidering”. Spidering platforms collect as many listings as possible from all individual suppliers in the market, usually free of charge and use this gathered information to extract revenue from buyer or advertisers. The main competitors of the dominant platform in the market under investigation apply this business model. So, they do not directly compete with the dominant platform through listing fees, but they do provide a valuable outside option to sellers and buyers which again is likely to prohibit the listing platform to exploit its dominant position.

4 Empirical Analysis

The analysis in this section proceeds as follows. First a value for all the exogenous parameters from the model presented above is derived from the data presented in the previous section, imposing additional assumptions where necessary for identification. Then, using these parameter values, the steady state matching equilibrium is simulated for the observed market allocation of buyers and seller. Finally, the counterfactual market outcomes are simulated should a Pigouvian planner and a monopolist set the service fees.

4.1 Deriving the model parameters from the data

Remember from section 2 that the exogenous parameters in the model are:

- B and S, the potential mass of buyers and sellers that participate to the platform, respectively.
- α and γ, the search and listing intensities of buyers and sellers, respectively.
- $1-\beta$ and β, the bargaining weight of buyers and sellers, respectively.
- The distributional parameters of $b \sim F^B(b)$ and $s \sim F^S(s)$, the buyer valuations and the reservation prices for a *homogeneous* real estate property.

4.1.1 Market size

To start, based on the administrative data reported in table 1, the total amount of sales of houses and apartments on weekly basis across the country in 2013 can be calculated:

$$(total\ sales\ houses\ +\ total\ sales\ apartments)/52 = 2336$$

This value is used as a proxy for both the mass of buyers B and sellers S that potentially patronize the listing platform on weekly basis. Note that this implicitly assumes that all buyers and sellers that contemplate purchasing or selling a property, respectively, will actually do so, either through the observed platform or through one of the competing matching channels, but no one remains unmatched. I thus ignore any buyers (sellers) that, for example, make a tradeoff between purchasing (selling) or renting and eventually make the decision to rent. The assumed market size should thus be interpreted as a conservative lower bound. In addition, assuming B and S are equal ignores any short-run fluctuations in the market and all results should be interpreted as long-run outcomes in which the market must be balanced. Consistently the matching outcomes and welfare analysis is evaluated at the simulated long-run steady state equilibrium, as discussed in greater detail below.

4.1.2 Listing and search intensities

Now, given that buyers are never charged for the service, assume that all buyers participate in the market through the observed listing platform. That is $N^B = B = 2366$.

The amount of sellers that participate N^S, which will be smaller than S given that the weekly listing fee $P^S = €4.8$ is positive, is not directly observable. A proxy, however, can be obtained for the number of novel listings being posted on weekly basis on the platform, γN^S. More specifically, using that a snapshot of the number of recent listings posted on the platform (that were online at most 15 days at this point) is observed in the cross section of total listings reported in table 2, the number of novel listings posted on weekly basis can be calculated as follows:

$$(((recent\ listings\ houses + recent\ listings\ apartments) * (1 - (1/average\ listing\ duration\ in\ weeks) * 2))/15) * 7$$

To obtain a value for this, a proxy for the average listing duration is required, which in turn can be obtained from the listing sample reported in table 3. The table shows that an average listing in the sample was online 14.3 weeks. This value is biased, however, given that the observation period is right censored at 20 weeks. Using standard survival analysis techniques, of which the details can be found in appendix 2.A, the online duration should the sample not be censored can be predicted, which results in a predicted value of 21.03 weeks. This in turn results in an estimate of a total of 5166 new listings being posted at the platform every week, i.e. $\gamma N^S = 5166$.

A proxy for γ, and thus for N^S, is simultaneously identified with the distributional parameters using the inverse demand equation for sellers (9), which can be written as:

$$p^S = \gamma P^S \frac{N^S}{M} = \beta \left(\int_{b^L}^{b^H} b f^B(b) db - F^{S^{-1}}(N^S/S) \right) \qquad (26)$$

in which the expected match duration of sellers N^S/M is proxied by the predicted listing duration, $N^S/M = 21.03$, and using that $P^S = 4.8$ and $N^S = 5166/\gamma$.

Once N^S, N^B and N^S/M are known, the buyer search intensity parameter α follows from rewriting the matching function (16):

$$\alpha = -\ln\left(1 - \frac{M}{N^S}\right)\frac{N^S}{N^B} \qquad (27)$$

4.1.3 Bargaining weights

Remember that the surplus when a seller type s and a buyer type b are matched is assumed to be efficiently divided among both parties through Nash-bargaining over the sales price. For simplicity, and given that there is no data available to get a proxy on this, assume that the bargaining game is symmetric. That is, the bargaining weight of both buyers and sellers is one half: $\beta = 1 - \beta = 0.5$. One could argue this assumption is reasonable given that buyers and sellers in real estate markets are essentially the same persons, merely taking up the role of buyer or seller at a different place at a different time, such that on aggregate the bargaining weights should balance out. However, other factors might play a role as well, like underlying asymmetries in reservation values or differences in information availability when taking up a different role, as well as the cyclical state of the market. For example, when the market is tight on the buyer-side, buyers perhaps possess more bargaining power than sellers. Harding, Rosenthal and

Sirmans (2003) and Merlo and Ortalo-Magné (2004) formally analyze the determinants of bargaining weights across buyers and sellers.

4.1.4 Distributional parameters

For symmetric bargaining weights the expression for the sales price bargained between a seller type s and a buyer type b for symmetric bargaining weights reduces to:

$$\rho(b,s) = \frac{1}{2}(b+s) \tag{28}$$

In addition, assume that the valuation of buyers for the real estate good is uniformly distributed over the interval $[b^L, b^H]$ and that the reservation price of sellers to provide the good to the market is uniformly distributed over the interval $[s^L, s^H]$. Furthermore, assume that the lower bound of buyer values is restricted such that $b^L = \frac{1}{2}(s^L + s^H)$ and that the upper bound of seller reservation prices is restricted to be $s^H = \frac{1}{2}(b^L + b^H)$. These assumptions imply that the distributions of buyer values and seller reservation prices can be summarized in the following scheme:

s^L $\qquad$ $b^L = \frac{1}{2}(s^L + s^H)$ $\qquad$ $s^H = \frac{1}{2}(b^L + b^H)$ $\qquad$ b^H

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|

$\tilde{s} = \frac{1}{2}(b^L + b^H) - 2p^S$

Note that the distributional parameters are chosen such that for free participation on both sides ($p^S = p^B = 0$) all potential sellers and all potential buyers will participate at the platform. However, as soon as the fee becomes positive on either side, some users will no longer participate. On the buyer-side, when p^B becomes positive, low value buyers will drop out first. On the seller-side, high reservation price sellers will decide not to participate when the listing fee becomes larger. From the data it is known that buyers are never charged, so they all participate, as was also assumed to derive the matching parameters. Sellers do are charged a listing fee in practice and hence they will not all participate. Only sellers with a reservation price smaller than or equal to $\tilde{s}$ participate and by the present assumptions $\tilde{s} = \frac{1}{2}(b^L + b^H) - 2p^S$, as also illustrated in the scheme above. So, the larger the listing fee, the fewer sellers post a listing on the platform.

Now, what do the assumptions of uniformly distributed buyer values and seller reservation prices imply for the distribution of sales price predicted by the model? To see this, first consider the case where all buyers and sellers participate at the platform ($p^S = p^B = 0$). Matching is assumed to be random, so b and s can be considered as i.i.d. random variables. We also know that $\rho = \frac{1}{2}(b + s)$, so the sales price is a fraction of the sum of two i.i.d. continuous uniform random variables. As formalized by Grinstead and Snell (1997), for example, this implies the sales price is distributed by a triangular distribution. Denote the density of the distribution of ρ as $g(.)$, which can be summarized as:

$$g(\rho) = \frac{4}{(b^H - b^L)(s^H - s^L)}\left(\rho - \frac{s^L + b^L}{2}\right), \text{if } \frac{s^L + b^L}{2} \leq \rho \leq \frac{s^L + b^H}{2}$$

$$g(\rho) = \frac{4}{(b^H - b^L)(s^H - s^L)}\left(\frac{s^H + b^H}{2} - \rho\right), \text{if } \frac{s^L + b^H}{2} \leq \rho \leq \frac{s^H + b^H}{2}$$

$$g(\rho) = 0, \text{ otherwise} \tag{29}$$

Note that expression (29) implies that the minimum sales price in the market is equal to $\rho_{min} = \frac{1}{2}(s^L + b^L)$, the maximum sales price satisfies $\rho_{max} = \frac{1}{2}(s^H + b^H)$ and the density reaches its top at $\rho_{mode} = \frac{1}{2}(s^L + b^H)$.

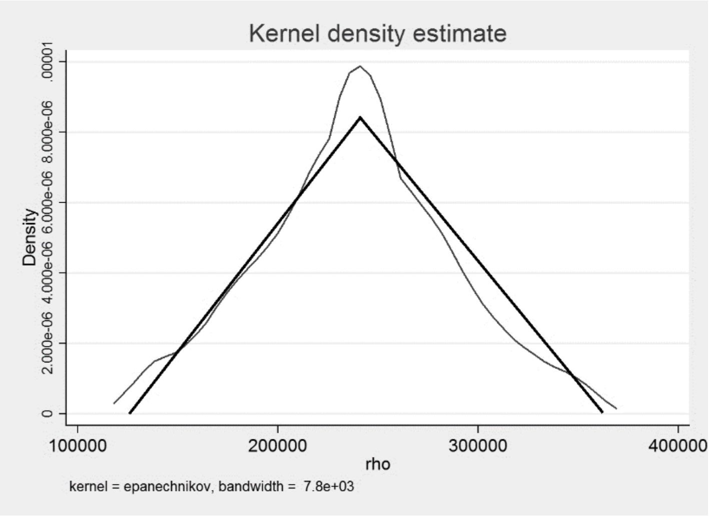
For the case not all sellers participate, s^H in expression (29) should be substituted for $\tilde{s} = \frac{1}{2}(b^L + b^H) - 2p^S$, in which case the density of ρ not only depends on the distribution parameters s^L, b^L, s^H and b^H, but also on the listing fee p^S. By also using the assumptions that $b^L = \frac{1}{2}(s^L + s^H)$ and $s^H = \frac{1}{2}(b^L + b^H)$ and using expression (26), it follows that observing ρ_{min} and ρ_{max} suffices to calculate the four distribution parameters, s^L, b^L, s^H and b^H, and the seller listing intensity parameter γ.

To obtain a proxy for ρ_{min} and ρ_{max}, I use the observed distribution of ask prices available from the listing sample reported in table 3. Two important issues have to be addressed here. Firstly, that the posted ask prices do not necessarily correspond with the eventual sales prices once the properties are sold. Furthermore, comparing the average actual sales prices in table 1 to the average ask-price in table 3 suggests that ask-prices are systematically higher that actual sales prices. To account for this, the average ask-price is calculated within the categories of houses and apartments and this is compared to the averages of actual sales prices. The ratio of sales price to ask-price for houses is about 0.80 and for apartments 0.86. This ratio is multiplied by the observed ask-price for each listing to get a proxy for the "expected sales price".

A second important issue is that real estate properties are not homogeneous in practice, as is assumed in the model. To control for the heterogeneous composition of the housing stock a hedonic price regression is estimated, in the spirit of Rosen (1974), with the expected sales price as dependent variable and the observable seller and property characteristics as covariates. The details of this regression can be found in appendix 2.B. The regression results shows that when controlling for property category (house or apartment), seller type (broker, notary or independent seller), property size and detailed location can explain up to 70% of the variation in expected sales prices. The remaining 30% of the variation will be interpreted as variation that comes from underlying buyer and seller heterogeneities in their valuations and reservation prices. To do so, the residuals of the hedonic regression are stored and added up by the average predicted value of the expected sales price across the sample to obtain a "composition adjusted" distribution of the expected sales price. To avoid biased results due to outliers, the minimum expected sales price, ρ_{min} in the model, is proxied by the 5th percentile of the distribution of the composition adjusted expected sales price. Similarly, the maximum expected sales price, ρ_{max} in the model, is assumed to correspond to the 95th percentile.

The grey line in figure 1 plots the Kernel density estimate of the observed distribution of the composition adjusted expected sales price, truncated at the 5th and 95th percentile. The black line plots the estimated distribution when constructed by the model.

Figure 1: Observed and estimated distribution of composition adjusted expected sales prices



The figure suggests that the assumption of linear buyer and seller demand fits the data reasonable well, although there is clearly still room for improvement. I use this linear approximation because it allows me to identify the listing intensity parameter γ, and thus the amount of sellers that participate in the market N^S, jointly with the distribution parameters. With richer data for Belgian real estate brokerage industry, chapter 4 of this dissertation presents a more refined specification of buyer and seller preferences derived from an observed distribution of sales prices, which unfortunately cannot be applied here by the limited data availability.

4.1.5 Obtained model parameters

Table 5 reports the values for all the model parameters obtained from the described procedure.

Table 5: model parameters

$N = S$	a	γ	β	s^L	b^L	s^H	b^H
2336	0.051	2.22	0.5	66897	184720	302540	420350

The results show that the search intensity parameter for buyers is 0.51, which implies that it takes about $1/\alpha \approx 20$ days for buyer to find a valuable trading platform on the platform. The listing intensity parameter is 2.22 which implies that an average listing is posted more than twice on the platform. More loosely interpreted this suggests that there are many listings present on the platform that never result in a match. For example, some sellers might post their listing independently first and subsequently through a broker or vice versa, which results in two posted listings but only one match. Or, sellers might re-post the same listing to maintain the tag "new listing". In addition, some sellers might post a listing without the intension to sell, just to explore the market value of their property, or may decide to rent their property instead of selling after a while. Whatever the underlying reason, the model assumes that none of the listings that eventually will remain unmatched cause additional congestion for the matching process. Should these listings cause additional congestion, the estimated matching elasticities reported below would be more unbalanced with a lower value for sellers and a higher value for buyers, which should be kept in mind.

In addition, table 5 shows that the reservation price of providing their (composition adjusted) real estate property to the market for sellers ranges from about €67000 to €300000. The valuation of buyers for the good ranges from approximately €185000 to €420000. Given that these values are large in magnitude compared to per-match listing fee that is incurred by sellers, $p^S = \gamma P^S N^S / M = €227$, the model predicts that there is almost full participation on the seller side: $N^S/S = 2332/2336 = 0.99$.

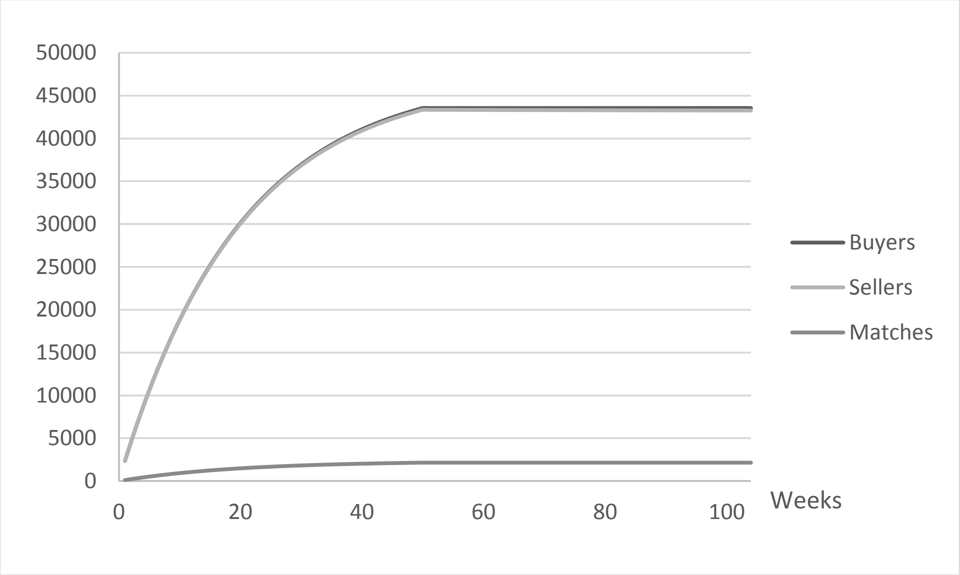
The estimated parameter values seem reasonable given the institutional and competitive setting described in section 3. By nature of the service the listing platform provides, additional revenues are made for every listing that is attracted and the platform is not necessarily concerned whether or not a listing actually results in the sale of a property, which can explain the large amount of “double” listings. In addition, the platform must keep the listing fees low to protect its dominant position in the market, which explains the large seller participation rate. A Pigouvian planner, in contrast, not only cares about the private platform revenues, but also about the number of matches that result from the platform service and about the surplus that these matches generate, which will result in very different socially optimal fees, than the ones observed in practice. Before turning to the derivation of the socially optimal service fees, however, the following subsection first simulates the steady state matching outcomes given the observed market allocation.

4.2 Steady state matching outcomes

The matching process until now was analyzed as a one-shot matching game, while in practice it is a dynamic process. Not just once, but every week about 5000 novel listings are posted on the platform and about 2300 new potential buyers enter the platform. Furthermore, sellers and buyers that were unmatched in a certain period not necessarily immediately leave the platform. Sellers have a contract with the platform about the listing duration and buyers are likely to search longer than one week. On the other hand, they will not stay on the platform forever and at some point buyers and sellers will be matched through one of the alternative matching channels available in the market (remember that almost all buyers and seller multi-home).

Assuming that buyers and sellers leave the platform after the same time period, the duration until exit can be simulated using the estimated parameter values and the observable snapshot of total amount of listings being posted on the platform, reported in table 2. More specifically, if at any given point in time there are 95724 listings posted on the platform, as shows by the table, it must be that buyers and sellers stay on the platform about 50 weeks for this number to be consistent with the predicted weekly matching outcomes. Figure 2 illustrates the convergence to the steady state outcome, starting from the one-shot matching game with 2332 sellers, 2336 buyers, a buyer search intensity of 0.05 and assuming that sellers and buyers exit after 50 weeks.

Figure 2: long-run outcomes repeated matching game



The figure shows that under this scenario the unique number of sellers that post listings on the platform converges to about 43000, which multiplied by the estimated listing intensity parameter $\gamma = 2.22$ is consistent with a steady state stock of listings of about 96000. In addition, the figure shows that that in the long-run there must also be about 43000 unique buyers searching the platform, which follows from the assumption that the market must be balanced (there can be no excessive stock of buyers and sellers). Given that there are about 240000 weekly visits are being logged on the platform, this suggests that an active buyer on average visits the platform about 5.5 times a week, which seems reasonable. Finally, the figure shows that the steady-state amount of matches generated through the platform converges towards 2150, which implies that a fraction $2150/2336 = 0.92$ of the total amount of matches that occur in the market are established through the observed listing platform. This again seems reasonable given the described institutional and competitive setting.

These numbers can also be used to calculate the steady state matching elasticities for buyers and sellers using expression (18) and that the steady state matching efficiency of buyers is $\alpha N^B/M = 1.02$. This results in a predicted matching elasticity for sellers of $\phi^S = 0.43$ and for buyers of $\phi^B = 0.57$. So, the platform is more efficient in matching buyers than sellers, but not that match. As noted above, accounting for the fact that some of the 'redundant' listings on the platform potentially cause additional congestion for the matching process would result in more unbalance estimates for the matching elasticities towards a lower value of ϕ^S and a higher value of ϕ^B.

4.3 Market distortions

Now that all the model parameters and steady state matching outcomes are known, the socially optimal listing fees can be calculated. To do so, the system of equations (24)-(25) reported in proposition 2.2 can be solved for the socially optimal allocation of buyers and sellers, which in turn is substituted in the expressions for inverse demand. Similarly, the optimal monopoly outcome follows from equations (21-22) in proposition 2.1. Table 6 shows the results.

Table 6: observed, socially optimal and monopoly outcomes

	Observed outcome	Socially optimal outcome	Monopoly outcome
N^S/S	0.99	0.70	0.47
p^S	227	46860	90149
N^B/B	1	0.80	0.53
p^B	0	41503	86578
M	2150	1645	1097
φ^S	0.57	0.57	0.57
φ^B	0.43	0.43	0.43
welfare	253760000	290785000	258480000
SS	126390000	68290000	30351000
BS	126880000	77105000	34269000
π	487000	145390000	193860000

The top rows in table 6 show that a Pigouvian planner would charge a much higher fee to both sellers and buyers than is currently observed in practice. The planner would attract only 70% of all potential sellers and 80% of potential buyers by charging them a per-match fee of about €47000 and €42000, respectively, rather than attracting approximately 100% of all sellers and buyers as is currently the case. As a result only a fraction $1645/2336 = 0.70$ out of the potential matches would occur through the platform. In addition, the last column in table 6 shows that a monopoly platform would charge an even higher fee than the social planner and would only attract 47% of the potential sellers and 53% of the potential buyers.

The bottom rows in table 6 show the amount of social value generated under the three scenarios and how this surplus is divided among the three parties of interest. Moving from the observed to the Pigouvian outcome would raise total surplus generated in the market on weekly basis from approximately

€254 million to €291 million. The main beneficiary of this transition would be the platform who's profits are raised vastly. The surplus attributed to sellers and buyers would be reduced, from €126 million to €68 million and from €127 million to €77 million, respectively. Whether a regulator would be willing to allow for such redistributions in surplus is of course a normative question. The monopoly outcome compared to the socially optimal outcome would further transfer surplus from both buyers and sellers to the platform and there would be a deadweight loss of about €32 million. Note, however, that the monopoly outcome comes closer to the social optimum than the observed market outcome. So, the results suggest that competition under the current market structure is too strong to appropriately account for the network externalities inherent to a one-to-one matching market.

Two final notes are in place about the results in table 6. Firstly, the outcomes are calculated for a constant buyer search intensity parameter α and seller listing intensity parameter γ. There is no reason to believe, however, why this parameter would remain constant when the allocation of buyers and sellers changes, especially when major shifts in the allocation would be carried through as proposed in table 6. For example, it might well be that buyers change their search behavior if less listings are available on the platform. I expect that buyers would start searching more intensively because of the increased per-period fee and increased competition among each other, which would be reflected in an increase of α. This would imply that the required increase in the fee charged to buyers would be less than the one calculated in table 6 to establish the social optimum. Similarly, should the listing fee charged to sellers increase, the search intensity of sellers would be likely to decrease, mitigating the loss in surplus to sellers estimated in table 6.

Secondly, the distribution parameters are calculated based on the residual variation in expected sales prices that could not be explained by the observables. The hedonic regression reported in appendix 2.B explains about 70% of the variation and the remaining 30% was interpreted as variation coming from underlying buyer and seller heterogeneities. Although property size and location are probably the most important attributes that explain the variation in property prices, there are other qualitative characteristics that are observable, but not taken up in the analysis. Examples of characteristics that do are observed in practice are the age of a property, whether or not it was recently renovated, whether or not there is a garden or a terrace, etc. Taking up these characteristics in the hedonic regression would reduce the estimated spreads between b^L and b^H and s^L and s^H. This in turn would render demand being more price elastic than currently estimated and would result in lower socially optimal and monopoly fees than reported in table 6.

For both these reasons the counterfactual fees should be interpreted as the upper bound of the actual fees that are required to establish the optimal allocations. Given that the current estimates are quantitatively large, however, neither of the reducing effects is expected to reverse the important qualitative result that the platform service fees are currently too low compared to the social optimum.

5 Conclusions

The first goal of this chapter was to apply the general platform pricing model developed in chapter 1 to the setting of a matchmaker that offers a listing service in a market for residential real estate. To do so, the model of chapter 1 was extended to allow for bargaining between matched buyers and sellers, such that the sales price of real estate properties is endogenously determined in the model. In addition, particular assumptions were imposed on the matching technology of the platform and the distributions of buyer and seller preferences, such that quantitative predictions could be made about the model outcomes for given parameter values. The second goal of this chapter was to take the model to the data. Data were collected from the largest online real estate platform in Belgium, based on which all the relevant parameters of the model were estimated or calculated. Then, using these parameter values, the observed market outcomes could be compared to the counterfactual outcomes of a Pigouvian planner and monopolist that optimally set the listing fee charged to sellers.

The results suggest that the observed service fees charged to buyers and sellers are significantly *below* the fees a Pigouvian planner would charge. The intuition is that the negative externalities that result from the matching and bargaining process are currently insufficiently internalized in the service fees. A monopolist would set even higher fees than the social planner. Nevertheless, the calculated monopoly outcome comes closer to the socially optimum than the observed outcome in practice. The results therefore suggest that, despite the fact that the observed platform clearly dominates the market, it can insufficiently exploit this dominant position in its fee setting to efficiently run the listing service by the presence of latent competition of alternative search channels available to buyers and sellers.

Quantitatively, the results should be interpreted with some caution. To be able to get a good and realistic estimate of the listing fees that would maximize social value generated in the market some further investigation is required. Providing sensitivity analysis for different assumptions made to derive the relevant model parameters is an important next step. In addition extending the model to allow for endogenous search and listing intensities is a promising direction for further investigation to obtain more nuanced results.

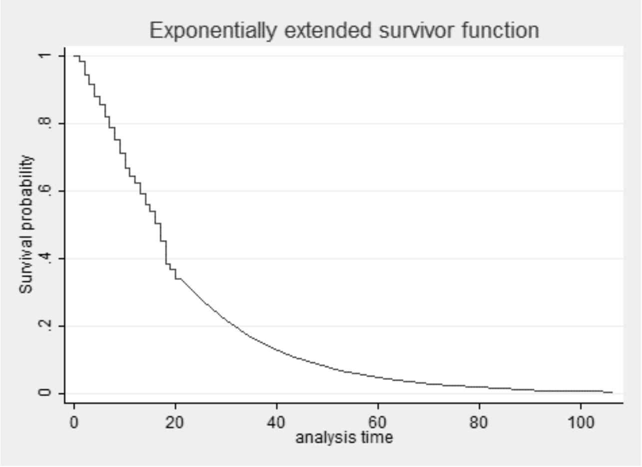
Appendix 2.A: Survival analysis

Table 3 in the main text shows that the average time a listing in the sample was online was 14.3 weeks. However, the observation period was terminated after 21 weeks, at which point 34% of the listings was still online. This problem can be viewed as a standard problem of right censored duration data. The expected time online taking the censoring into account can be calculated using standard duration analysis techniques. More specifically, the weekly survivor function of listings (when a listing is taken offline means death) can be estimated non-parametrically following Kaplan and Meier (1958) up to the censoring point. Beyond this point the survivor function can be extended to zero by using an exponentially fit curve and the "extended mean" of survival (or expected time online) can be calculated from the surface below the entire survivor function, following Klein and Moeschberger (2003).[5]

The expected time online that follows from this procedure is 21.03 weeks, which is significantly above the sample average of 14.3 weeks. Figure A.1 plots the estimated Kaplan-Meier survivor function with the exponential extension, suggesting that this specification to estimate the extended mean seems reasonable.

[5] See, Cleves, Gould, Gutierrez and Marchenko (2010) for a useful practical guide to implement this procedure in Stata.

Figure A.1: Kaplan-Meier survivor function of online listing durations with exponential extension



Appendix 2.B: Hedonic regression

Table B.1 reports the results for the OLS estimates, controlling for possibly heteroskedastic standard errors, of the expected sales price on various covariates.

Table B.1: hedonic regressions expected sales price

Dependent variable: expected sales price					
Covariates:	(1)	(2)	(3)	(4)	(5)
category	50215	52482	-67149	-36655	-31225
	(3563)	(3586)	(4641)	(4483)	(4680)
agency		12504	9205	4402	4759
		(4269)	(3798)	(3508)	(3604)
notary		-41367	-6020	-11450	-8100
		(6150)	(12139)	(12040)	(8336)
bedrooms			17686	14631	12314
			(2798)	(2643)	(2708)
size			1072	1038	1025
			(50)	(48)	(48)
district dummies	No	No	No	Yes	No
zip-code dummies	No	No	No	No	Yes
constant	196847	187967	47836	69252	134005
	(2707)	(4253)	(6041)	(6813)	(22645)
R^2	0,023	0,030	0,469	0,556	0,709
obs	6712	6712	4735	4735	4735

The first column in table B.1 shows that houses on average are expected to sell more expensively compared to apartments. The second column in addition controls for seller type. Real estate agents are expected sell at a higher price and notaries at a lower price compared to independent sellers. However, these differences become insignificant when controlling for additional property characteristics. Column 3 controls for property size by taking up the number of bedrooms and living surface. Note that the coefficient of category becomes negative and significant when controlling for size. So, per square meter of living surface, apartments are expected to be more expensive than houses. Finally, columns 4 and 5 control for the location of properties at the level of districts and zip-codes, respectively.

Chapter 3

Proportional Service Fees as a Selection Tool[1]

1 Introduction

In a broad range of markets, the use of fees charged proportional to an observed outcome of market transactions, possibly combined with a flat fee, is prevalent among some service providers that facilitate transactions, whereas others refrain from charging a proportional fee and simply charge a uniform price for their service. For example, real estate brokers in the US typically charge a commission rate up to 6% proportional to the sales price of properties, recently often combined with a flat fee component (e.g. Hsieh and Moretti (2003), USDOJ-FTC report (2007)[2]). Credit card issuers like Visa and MasterCard typically charge a proportional fee ranging from 1% to 2.5%, sometimes combined with a small per-transaction fee, whereas debit card issuers usually charge a flat per-transaction fee, although for the latter there has recently also been a shift towards the use of proportional fees (e.g. Shy and Wang (2011), Wang and Wright (2014)). Online market places like eBay and Amazon usually charge a relatively large proportional

[1] This chapter is single-authored and presents new material, although some parts of the analysis already appeared in a previous working paper version of Goos, Van Cayseele and Willekens (2014) in different form. By limitation of space and a different focus, however, we decided to drop the analysis from that paper and it is therefore treated now as a separate chapter in this dissertation.

[2] See Delcoure and Miller (2002) for an overview of real estate brokerage fees charged in other industrialized countries.

fee and small flat fee per transaction (e.g. Amazon typically charges 15% + $1.35, as reported by Wang and Wright (2014)). Apple and Google charge application developers a fee up to 30% and no flat fee (e.g. Muthers and Wismer (2012)). Labor market intermediaries sometimes charge a fee proportional to the wage of a worker, like temporary help agencies and headhunters, but other agencies often only charge a flat fee for a job placement. More traditional market places like shopping malls, festivals and amusement parks that also connect consumers/visitors and merchants rarely charge proportional fees. Other examples of platforms that connect different types of consumer groups in return for a flat per-transaction fee can be found in the two-sided markets literature (e.g. Rochet and Tirole (2003, 2006), Rysman (2009), Evans and Schmalensee (2013)).

A natural question that arises is why some service providers charge solely a proportional fee, some charge a fee with both a flat component and a proportional component, whereas others simply charge a flat per-transaction fee. This chapter sheds new light on this question by modeling a monopoly service provider that aims to attract consumers that are heterogeneous in two dimensions. One dimension of consumer heterogeneity becomes observable to the monopolist once the service is provided and the service provider possibly charges a fee proportional to its revealed value. The other dimension of heterogeneity never becomes revealed to the monopolist and remains private information to consumers. The valuation of consumers is allowed to flexibly depend on both consumer types and the service provider possibly also charges a flat fee on top of (or instead of) the proportional fee.

In this setting, it is shown that the service provider only charges a positive proportional when the usage of such a fee results in "advantageous selection" of consumers into the market and will refrain from using this fee type when it induces "adverse selection". Advantageous selection occurs when consumers with the highest observable types are also the ones with the highest willingness to pay for the service. I use the terminology "adverse" and "advantageous" selection given the equivalence of its use in the information economics literature (e.g. Akerlof (1970)). For example, an insurance market is typically said to be characterized with adverse (advantageous) selection when consumers with the highest (lowest) willingness to pay are also the ones most costly to serve. Equivalently, in the present setting I interpret the market to be characterized by adverse (advantageous) selection when consumers with the highest (lowest) valuation for the service are the ones least (most) valuable to the service provider, reflected by a low (high) value of the observable consumer type.

On top of the selection effect of marginal versus inframarginal consumers, it is shown that the usage of a proportional fee also unambiguously induces "adverse sorting" within the group of marginal consumers attracted by the monopolist. The importance of this sorting effect at the margin has only recently been emphasized in the literature on selection markets by Veiga and Weyl (2013a,b) and only appears in the presence of multidimensional consumer heterogeneities. In the present setting, sorting within the group of marginal consumers (who all have the same unobserved type) is unambiguously adverse because consumers with the highest disutility for the proportional fee (those with the highest observable types) are also the ones most valuable to the service provider, which makes the monopolist reluctant to use the proportional fee. Intuitively, it is shown that only a proportional fee and no flat fee is used when the intensive advantageous selection effect outweighs the adverse sorting effect at the margin. If not, the service provider uses both fee types (or only a flat fee when there is adverse selection). These stylized results are further illustrated using two specific examples. One of a competitive labor market in which workers receive a wage and fringe benefits, where an intermediate service provider can only charge a fee contingent on the wage and not the benefits. The other of a competitive multiple goods market with proportional consumer demand à la Wang and Wright (2014) extended to allow for fixed consumer benefits.

A second important question is how the use of proportional fees affects welfare. It is shown that a Pigouvian planner never charges a proportional fee, independent of the selection and sorting effects it induces, and always simply equates the flat fee to marginal cost. The rationale for this is well-known from the monopoly third-degree price discrimination literature (e.g. Schmalensee (1981), Aguirre, Cowan and Vickers (2010)). When the marginal cost of serving different consumer groups is the same, charging different prices across consumer groups results in a "misallocation effect" and is socially inefficient. To explore whether or not the use of a proportional fee by a private monopolist is socially harmful, I further build on established results from this literature. It is shown that the welfare effects of allowing a monopolist to use a proportional fee are identical to allowing a monopolist to third degree price discriminate when there are only two observable consumer types. This result does not generalizes to a setting with multiple or a continuum of observable consumer types, however, given that a monopolist that can only use two pricing instruments (a flat and proportional fee) to discriminate across more than two consumer groups is more restricted than a monopolist that can freely charge a different uniform price for each of these consumer groups. I am still working on conditions under which the usage of proportional fees tends to reinforce or mitigate the familiar welfare effects of third-degree price discrimination.

In the literature, there is a recent strand of research that addresses the question why service providers make use of proportional fees, usually applied to a specific market in which the usage of such fees is common. For example, Loertscher and Niedermayer (2012, 2013) investigate the effectiveness of the use of proportional fees in a dynamic random matching model with buyer-seller bargaining with an application to real estate brokerage. Shy and Wang (2011) provide a rationale for payment card networks to use proportional fees when merchants possess market power. Muthers and Wismer (2012) justify the use of proportional fees in online market places as a commitment instrument for platforms not engage in competition with attracted merchants.

Wang and Wright (2014) justify the use by the argument that it allows for efficient price discrimination. As in the present paper, Wang and Wright (2014) also establish the link between proportional fee pricing and third-degree price discrimination. Furthermore, in their specific model of a multiple goods market with proportional consumer demand the equivalence holds for any number of goods being traded in the market. As argued above, however, this result does not hold in general.

Notably, both Loertscher and Niedermayer (2013) and Wang and Wright (2014) address an even broader question than the one investigated here in the sense that they investigate under which conditions the use of a “linear” or “affine” service fee (consisting of a flat and proportional component) is preferred over a more complex ad valorem fee schedule. In both papers these conditions are linked to the properties of the one-dimensional distributions of valuations of attracted consumers.

In contrast, the present paper takes as given that the service fee consists of a simple flat and proportional component and instead allows for more flexible two-dimensional consumer types of which one dimension never becomes revealed to the service provider. None of the aforementioned papers allows for this and therefore the selection and sorting effects emphasized here do not appear in these papers. As mentioned, these effects have only recently been uncovered for selection markets by Veiga and Weyl (2013a,b), who are able establish their results by proposing a new methodology to tackle complicated multi-dimensional screening problems by using simple calculus through a generalized version of Leibniz’s integral rule. This methodology is also applied to establish the results in the present paper.

The remainder of this chapter is built up as follows. Section two presents the model. Section 3 analyses the monopoly outcomes. Section 4 presents the welfare analysis. Section 5 discusses extensions and section 6 concludes.

2 Model

Consider a monopolist that provides a service in a market with a unit mass of potential consumers. Consumers have two-dimensional types, denoted by the vector $(\theta, \mu) \in [\theta_L, \theta_H] \times [\mu_L, \mu_H] \subseteq \mathbb{R}_0^+ \times \mathbb{R}$, distributed according to the density function $f(\theta, \mu)$, assumed differentiable in both arguments. Consumer willingness to pay for the service is given by the function $v(\theta, \mu)$, differentiable in both arguments. Assume θ can be expressed in monetary terms, while μ can take on both a monetary or a non-pecuniary subjective value. The nature of the service is such that θ and μ are both private information to consumers *ex ante*, when the fee charged in return for the service is announced by the monopolist and when consumers subsequently decide whether or not to purchase the service. However, *ex post* the value of θ becomes observable to the monopolist once the service is provided (while μ remains private information) and the service fee is possibly contingent on the revealed value of θ. More specifically, assume that the service fee consists of two components, a flat component T, referred to as the flat fee, and a proportional component t, referred to as the proportional fee, such that consumer utility can be written as:

$$u(T, t) = v(\theta, \mu) - t\theta - T \tag{1}$$

For the exposition of the model, and in the examples used to illustrate the model below, I maintain the assumption that $v(\theta, \mu)$ is monotonically increasing in μ, such that consumers participate when $\mu \geq v^{-1}(\theta, T +$

$t\theta) \equiv \hat{\mu}(T, t, \theta)$.[3] As formalized by Veiga and Weyl (2014a), demand can then be expressed as the following iterated integral:

$$q(T,t) = \int_{\theta_L}^{\theta_H} \int_{\hat{\mu}(T,t,\theta)}^{\mu_H} f(\theta,\mu) d\mu d\theta \qquad (2)$$

Assume that the monopolist incurs a constant marginal cost $c \geq 0$, such that profits of the service provider can be expressed as:

$$\pi(T,t) = (T + t\bar{\theta}(T,t) - c) q(T,t) \qquad (3)$$

where $\bar{\theta}(T,t)$ denotes the average observable consumer type, defined as:

$$\bar{\theta}(T,t) \equiv \frac{1}{q(T,t)} \int_{\theta_L}^{\theta_H} \int_{\hat{\mu}(T,t,\theta)}^{\mu_H} \theta f(\theta,\mu) d\mu d\theta \qquad (4)$$

Total social value generated in the market, defined as the sum of total consumer utility and profits, is equal to:

$$W(T,t) = \int_{\theta_L}^{\theta_H} \int_{\hat{\mu}(T,t,\theta)}^{\mu_H} v(\theta,\mu) f(\theta,\mu) d\mu d\theta - cq(T,t) \qquad (5)$$

Before turning to the optimal pricing decision of the monopolist, first consider two stylized examples of markets that satisfy the assumptions of the presented model, which will be used to illustrate the intuition of the

[3] More generally, it suffices that there exists a unique value of either θ or μ above or below which consumers participate. With proper adjustment of the expressions for demand, profits and welfare, the same methodology can be used to derive the results of the model. In addition, the analysis also readily extends any finite dimension consumer types. For some applications, for example, it might be required that μ is a vector rather than a scalar. In this case it suffices that there is one component of μ that uniquely determines the cutoff of participation. See, Veiga and Weyl (2014a) for further details on this.

results throughout the analysis. Further extensions and other applications are discussed in section 5.

Example 1 *Competitive labor market with fringe benefits*

Consider a labor market with a unit mass of firms and workers. Firms are heterogeneous in their productivity levels y. I abstract from any capital investments and assume that firms are competitive in the sense that workers get paid the value of their productivity. The payment to a worker possibly consists of a wage w and various fringe benefits with value x, such that $y = w + x$. The service provider is a monopoly platform that provides a service of matching workers to firms and the service fee is possibly contingent on the wage earned by workers, but not on the fringe benefits. Given that firms are perfectly competitive, the incidence of the service fee falls on workers, independent to which side of market it is charged. Ignoring any frictions that might arise from the matching process and normalizing the reservation wage of workers to zero, worker utility can be written as $u(T,t) = (1-t)w + x - T$. In the notation of the general model above $w = \theta$, $x = \mu$ and $w + x = v(\theta, \mu)$ and all the expressions for demand, profits and welfare can be adjusted accordingly.

Example 2 *Competitive multiple goods market with fixed consumer benefits*

This example presents a simplified version of the multiple goods market model with proportional consumer demand of Wang and Wright (2014), extended to allow for fixed consumer benefits. Sellers provide goods to the market that are heterogeneous in cost or "scale", denoted by s. For each scale type there are at least two sellers who engage in Bertrand competition to provide the good to the market, such that price equals cost: $s = p$. For each of the goods traded there is a unit mass of consumers with unit demand and consumer valuation for a good is proportional to the scale of the good: $s(1 + b)$. Wang and Wright (2014) assume that consumers are heterogeneous in b. Instead, I assume here that b is the same across consumers (and sufficiently large such that all goods are traded), but that they also have a fixed benefit B to participate in the market, which is allowed to differ across consumers. The model readily extends to consumers being heterogeneous in both dimensions, however, this additional complexity is not necessary to capture the important intuitions below. A monopoly platform organizes the market and can charge sellers to participate, possibly contingent on the price of the goods being sold. The incidence of the platform fee, however, falls on consumers because sellers are perfectly competitive. Equivalently, the flat fee can also be charged directly to consumers to participate in the market, depending on the application. In the general notation $p = \theta$, $B = \mu$ and $(1 + b)p - p + B = v(\theta, \mu)$. Consumer utility can thus be written as: $u(T, t) = (b - t)p + B - T$. So, the platform fee determines how many consumers participate in each market. Note that the expressions for demand, profits and welfare must be multiplied by the number (or mass) of goods being traded in the market given that there is a unit mass of consumers for each good.

3 Monopoly pricing

This section derives the optimal monopoly service fee and investigates under which conditions the fee is composed of a flat component, a proportional component, or both.

3.1 The optimal service fee

Using the generalized version of Leibniz's integral rule proposed by Veiga and Weyl (2014a) to differentiate multidimensional integrals, the first-order condition of the monopolist that maximizes profits with respect to T can be written as:

$$T + t\tilde{\theta}(T,t) - c = \frac{q(T,t)}{\tilde{q}(T,t)} \tag{6}$$

where $\tilde{q}(T,t)$ denotes the density of marginal consumers, defined as:

$$\tilde{q}(T,t) \equiv \int_{\theta_L}^{\theta_H} \frac{f\big(\theta,\hat{\mu}(T,t,\theta)\big)}{\partial v\big(\theta,\hat{\mu}(T,t,\theta)\big)/\partial\mu}\, d\theta \tag{7}$$

and $\tilde{\theta}(T,t)$ denotes the average observable consumer type across marginal participants, defined as:

$$\tilde{\theta}(T,t) \equiv \frac{1}{\tilde{q}(T,t)} \int_{\theta_L}^{\theta_H} \theta\, \frac{f\big(\theta,\hat{\mu}(T,t,\theta)\big)}{\partial v\big(\theta,\hat{\mu}(T,t,\theta)\big)/\partial\mu}\, d\theta \tag{8}$$

Note that there is not a representative marginal consumer type, as in models with one-dimensional consumer heterogeneity. Instead, marginal consumers differ in their observable types and the monopolist accounts for the *average* marginal type in the optimal pricing equation.[4] More specifically, expression (6) shows that the monopolist, for a given t, chooses T such that the marginal service fee (equal to the sum of the flat fee and the average revenue extracted from marginal participants through t) over marginal cost is equated to the ratio of consumer demand over the density of marginal consumers. This ratio is the equivalent of the inverse hazard rate of demand in a setting of two-dimensional consumer types. As one would expect, for $t = 0$ expression (6) collapses to the standard Lerner condition $(T - c)/T = 1/\varepsilon$, where $\varepsilon \equiv -Tq'(T)/q(T)$ is the elasticity of demand with respect to T.

The first-order condition with respect to t can be written as:

$$T + t\tilde{\theta}(T,t) - c = \underbrace{\frac{\bar{\theta}(T,t)}{\tilde{\theta}(T,t)}}_{\substack{Intensive \\ selection\ effect}} \; \frac{q(T,t)}{\tilde{q}(T,t)} - \underbrace{\frac{t\widetilde{\sigma_\theta^2}(T,t)}{\tilde{\theta}(T,t)}}_{\substack{Sorting\ effect \\ at\ the\ margin}} \qquad (9)$$

where $\widetilde{\sigma_\theta^2}(T,t)$ denotes the variance of observable types across marginal consumers, defined as:

$$\widetilde{\sigma_\theta^2}(T,t) \equiv \frac{1}{\tilde{q}(T,t)} \int_{\theta_L}^{\theta_H} \theta^2 \frac{f\big(\theta, \hat{\mu}(T,t,\theta)\big)}{\partial v\big(\theta, \hat{\mu}(T,t,\theta)\big)/\partial\mu} d\theta - \tilde{\theta}^2 \qquad (10)$$

[4] Furthermore, note that weights by which the average marginal type is calculated, is not just the density function evaluated at $\hat{\mu}(T,t,\theta)$. In addition, marginal types must be normalized by the effect of the unobservable type on consumer willingness to pay ($\partial v\big(\theta, \hat{\mu}(T,t,\theta)\big)/\partial\mu$)) because μ is not necessarily expressed in monetary terms. This weighting is important when consumer willingness to pay is not quasi-linear in μ, which is possibly the case in the present model, and has previously been overlooked in the literature, as emphasized by Veiga and Weyl (2014a).

Expression (9) shows that the monopolist accounts for two additional effects when determining the optimal value of t compared to the optimal choice for T. Both effects reflect how the platform accounts for the fact that changing the proportional fee changes the composition of consumers selected into the market. Firstly, the *intensive selection effect* captures that lowering the proportional fee reduces the revenue extracted from inframarginal consumers ($\bar{\theta}(T,t)q(T,t)$), whereas it implies a gain in revenues at the margin ($\tilde{\theta}(T,t)\tilde{q}(T,t)$). When the intensive loss is larger relative to the gain at the margin, the monopolist is more reluctant to reduce the proportional fee to attract additional consumers and hence this tends to push up the markup of the marginal service fee over marginal cost, as the effect appears positively in the right hand side of expression (9). This effect is not present under uniform pricing because then the surplus extracted from marginal and inframarginal consumers is the same.

Secondly, the *sorting effect at the margin* captures that reducing the proportional fee, on top of the gain in revenues at the margin from attracting these consumers ($\tilde{\theta}(T,t)\tilde{q}(T,t)$), implies a further gain because there is "adverse sorting" within the set of marginal consumers, captured by ($-t\widetilde{\sigma_{\theta}^{2}}(T,t)\tilde{q}(T,t)$). That is, reducing the proportional fee attracts marginal consumers with a higher θ (the ones with the highest disutility for the proportional fee within the set of marginal consumers, who all have the same μ) and these are precisely the consumers most valuable to the monopolist. All else equal, this effect therefore pushes down the markup of the marginal service fee over marginal cost, as it appears negatively in the right hand side of expression (9). The effect is larger when there is more heterogeneity in observable consumer types across the marginal consumers, measure by the variance of θ for marginal consumers ($\widetilde{\sigma_\theta^2}(T,t)$). Again, this effect is not present under uniform pricing because then all marginal consumers have the same value to the monopolist.[5]

When a unique interior solution exists, the optimal flat and proportional fee charged by the monopolist, denoted by T^* and t^* respectively, is the solution to the system of equations (6) and (9).[6] In addition, denote the optimal flat fee when the proportional fee is (exogenously or endogenously) equated to zero as T^0. Similarly, denote the optimal proportional fee when the flat fee is equal to zero as t^0.

[5] The sorting effect at the margin described here is a specific characterization of a more general result derived by Veiga and Weyl (2014b). They show that when a monopolist chooses a product characteristic in the presence of multi-dimensional consumer heterogeneity, the effect at the margin of changing the product characteristic on profits is equal to the density of marginal consumers times to the covariance, among marginal consumers, between the marginal effect of the product characteristic on willingness to pay and the cost of providing the good to these consumers. In the present setting, the sorting effect collapses to a term proportional to the variance of θ among marginal consumers because θ captures both marginal disutility of consumers and the (negative) cost to the monopolist from changing t.

[6] By the Hessian test, the second-order restrictions for the monopoly maximization problem to be locally concave are

$$\frac{\partial^2\pi}{\partial T^2}, \frac{\partial^2\pi}{\partial t^2} < 0 \text{ and } \frac{\partial^2\pi}{\partial T^2}\frac{\partial^2\pi}{\partial t^2} > \frac{\partial^2\pi^2}{\partial T \partial t} \equiv \chi^2$$

When globally satisfied $\forall T, t \geq 0$, the solution to the system (6) and (9) exists and is unique. Following Weyl (2010), who derives second-order restrictions for a monopoly platform that optimally chooses two quantities, sufficient and necessary conditions for this are that $f(\theta,\mu)$ satisfies the following conditions for any $c \geq 0$: (i) $\rho_T \equiv \frac{dT}{dc}|_t > 0, \rho_t \equiv \frac{dt}{dc}|_T > 0$ and (ii) $\tilde{\theta}\tilde{q}^2 > \rho_T\rho_t\chi^2$. When condition (i) is violated for one of the pricing instruments, and hence the monopoly equates that instrument to zero (the pass-through of cost is zero or negative), the sufficient and necessary condition for the model to yield a unique solution is simply that profits are globally concave in the other pricing instrument, which is assumed to be satisfied.

3.2 The optimal composition of the service fee

Proposition 3.1 derives conditions for the optimal pricing incentives of the monopolist in terms of usage of the different pricing instruments available. The results follow from differentiating profits with respect to each pricing instrument, allowing the other pricing instrument to be dependent on its value, and using that totally differentiating the expression for demand (2) with respect to T and t yields $dT/dt = -\tilde{\theta}(T,t)$.

Proposition 3.1 *The monopolist uses a positive proportional fee as a pricing instrument when it induces "advantageous selection" of consumers. That is,*

$$\frac{\partial \pi(T^0(t),t)}{\partial t} > 0 \Leftrightarrow \bar{\theta}(T^0) - \tilde{\theta}(T^0) > 0 \tag{11}$$

The monopolist only uses a positive proportional fee and no positive flat fee when the intensive advantageous selection effect is sufficiently large relative to the adverse sorting effect at the margin. That is,

$$\frac{\partial \pi(T,t^0(T))}{\partial T} < 0 \Leftrightarrow \left(\bar{\theta}(t^0) - \tilde{\theta}(t^0)\right) q(t^0) > t^0 \widetilde{\sigma_\theta^2}(t^0)\tilde{q}(t^0) \tag{12}$$

Proposition 3.1 shows that, evaluated at the optimal monopoly outcome when $t = 0$, the service provider can further increase profits by substituting a small piece of the flat fee with a positive proportional fee (keeping demand fixed) if and only if the use of this proportional fee advantageously selects consumers into the market. That happens when the average observable consumer type across all consumers is larger than the average across marginal consumers. Or, in other words, when consumers with the highest valuation for the service are also the ones most valuable to the monopolist. When usage of a proportional fee induces consumers to adversely select into the market, it is not profitable for the monopolist to use this pricing instrument.

In addition, the proposition shows that, evaluated at the optimal monopoly outcome when $T = 0$, the service provider has no incentive to substitute some of the proportional fee for a positive flat fee (keeping demand fixed) when the advantageous selection effect is sufficiently large compared to adverse sorting effect at the margin. Remember from the discussion of the optimal pricing equation for the proportional fee (9) that, all else equal, a larger adverse sorting effect at the margin tends to push down the optimal markup of the marginal service fee over marginal cost, whereas a greater intensive advantageous selection effect (a larger $\bar{\theta}(t^0)/\tilde{\theta}(t^0)$) tends to push up the margin. This tradeoff is also reflected in the optimal choice between the use of the two types of pricing instruments. When intensive advantageous selection induced by the use of the proportional fee is sufficiently large compared to the adverse sorting effect at the margin, the monopolist will only use the proportional fee and no flat fee. Otherwise, the monopolist uses both fee types.

3.3 Signing the selection effect

A natural question that arises at this point is: what determines the sign and the degree of intensive selection and the degree of adverse sorting at the margin? The answer lies in the properties of the joint distribution of observable and unobservable types. To see this, first consider the case where consumers are only heterogeneous in unobservable types μ and there is no heterogeneity in the observable consumer type θ. In this case there is no intensive selection effect and no sorting effect at the margin and the monopolist is indifferent between the two fee types. In this case the value of $t\theta$ is the same for all consumers changing its value through t affects consumer utility and monopoly profits in precisely the same as changing the flat fee T by the same amount.

At the other extreme, consider the case where consumers are only heterogeneous in observable types θ and there is no unobserved heterogeneity in μ. Then, by assumption, $v(\theta)$ must be monotonically increasing in θ and when $t = 0$ high observable consumer types will enter the market first. Hence, the market is characterized by advantageous selection and condition (11) in proposition 3.1 is satisfied. Furthermore, when there is only heterogeneity in θ, there is a single marginal observable type and there is no sorting at the margin. Hence, condition (12) for the monopolist to only use a proportional fee and no flat fee simplifies to $\bar{\theta}(t^0) - \tilde{\theta}(t^0) > 0$. So, in the case of one-dimensional heterogeneity in θ, the monopolist always charges a proportional fee (given that $\bar{\theta}(T^0) - \tilde{\theta}(T^0) > 0$) and will do so up to the point where further raising this fee induces adverse selection (or reduces profits when $\bar{\theta}(t^0) - \tilde{\theta}(t^0) > 0$).

For intermediate cases, the sign of the intensive selection effect crucially depends on the correlation between observable and unobservable consumer types. To illustrate this, consider again the examples presented in section 2. Example 1 considered a competitive labor market with fringe benefits in which worker utility to purchase the service was $u(T, t) = (1 - t)w + x - T$, where w is the worker wage and x is the value of the fringe benefits, and competitive firms simply pay the worker the value of its productivity $y = w + x$. In this example there is adverse selection when high productivity workers earn a lower wage than low productivity workers and instead get compensated through additional fringe benefits. This type of adverse selection might be a real threat to intermediate service providers in labor markets that want to charge a commission proportional to the wage of a worker, but are unable to control the determination the fringe benefits of the employment contracts. That is, when the service provider charges a positive proportional fee, the worker might ask the firm to substitute some of the wage for fringe benefits. This would raise utility of the worker, the firm would be indifferent and this undermines the pricing strategy of the service provider.

Example 2 considered a competitive multiple goods market with buyer utility to purchase one of the goods in the market equal to $u(T, t) = (b - t)p + B - T$, where b is a constant markup of consumer valuations over sales prices p and B is a fixed consumer benefit to participate in the market. In this example, when there is no heterogeneity in B, the service provider always charges a proportional fee by the result in proposition 3.1. There are indeed many markets or marketplaces in which service providers facilitate transactions between buyers and sellers in which fixed consumer benefits are not expected to play an important role and where proportional fee pricing is prevalent. Examples are real estate markets where brokers facilitate transactions, online marketplaces like eBay or Amazon and payment card networks. Other types of service providers that operate markets or market places in which fixed consumer benefits are important, however, might again be faced with a problem of adverse consumer selection if they want to use proportional fees as a pricing instrument. Examples are shopping malls, festivals and amusement parks. Consider a music festival, for example, that possibly charges an entry fee T to visitors and the organizer wants to make additional profits by charging sellers to set up stands for food, drinks and other goods. The organizer might contemplate to charge sellers a fee proportional to the sales price of each good sold. The latter pricing strategy will be most profitable when consumers who highly value the music are also the ones who purchase expensive goods in the festival marketplace. However, if these consumers are the ones who purchase the least expensive goods, more profits might be extracted by charging a higher entrance fee.

4 Pigouvian pricing and the effect of proportional fees on welfare

This section derives the optimal service fee chosen by a social planner that maximizes total social value generated in the market and investigates under which conditions the usage of a proportional fee in the private market increases or reduces welfare compared to the case when the usage of such a fee is prohibited.

4.1 The socially optimal service fee

Using the same methodology as above, the first-order condition of a social planner that maximizes total social value, given by expression (5), with respect to T can be written as:

$$T - t\tilde{\theta}(T,t) - c = 0 \tag{13}$$

The Pigouvian planner thus chooses the optimal flat fee such that the marginal service fee is equated to marginal cost. Similarly, the first-order condition with respect to t can be written as:

$$T - t\tilde{\theta}(T,t) - c = -\underbrace{\frac{t\widetilde{\sigma_\theta^2}(T,t)}{\tilde{\theta}(T,t)}}_{\substack{Sorting\ effect \\ at\ the\ margin}} \tag{14}$$

Compared to the incentives of the monopolist, the Pigouvian planner also accounts for the sorting effect at the margin, but not for the intensive selection effect. It directly follows from (13) and (14) that the only possible solution for the composition of the optimal Pigouvian service fee is $T^W = c$ and $t^W = 0$. So, the Pigouvian planner never uses the proportional fee to select certain types of consumers into the market and prefers that all consumers are served at marginal cost, independent of their specific types.

The result that a welfare maximizer never charges different prices across different types of consumer groups when the cost of serving them is the same is well-known from the third-degree price discrimination literature and is usually referred to as the misallocation effect (e.g. Stole (2007), Aguirre, Cowan and Vickers (2010)). That is, for a given amount aggregate consumption, price discrimination drives a wedge between willingness to pay of marginal consumers across different market segments such that some consumers with a relatively low willingness to pay replace consumers with a relatively high willingness to pay compared to the allocation under the nondiscriminatory price. In the present setting, each observable consumer type θ can be thought of as a separate market segment and the usage of proportional fees implies that different consumer types are charge different service fee $T + t\theta$, which thus results in allocative inefficiencies given that the marginal cost to serve all consumer types is the same.

4.2 The effect of private proportional fee usage on welfare

The fact that the usage of a proportional fee results in allocative inefficiencies, does not necessarily implies that banning proportional fees from a private market necessarily improves welfare. Again, as is well-known from the third-degree price discrimination literature, allowing a monopolist to price discriminate might improve welfare if it increases aggregate consumption in the market, usually referred to as the output effect. When the output effect outweighs the misallocation effect, allowing for price discrimination might be welfare improving. Aguirre, Cowan and Vickers (2010) show that whether or not this is the case crucially depends on the relative curvatures of demand across the different market segments. It can be shown that precisely the same welfare criteria for monopoly third-degree price discrimination to be welfare improving apply to the present setting when there are only two observable consumer types, as formalized in lemma 3.1.

Lemma 3.1 *When there are only two observable consumer types* (θ_L, θ_H)*, the welfare effect of prohibiting a monopoly service provider to charge consumers a fee proportional to the value of their observable types is identical to prohibiting a monopolist to third-degree price discriminate based on observable consumer types, i.e. to charge a different uniform price to consumer groups segmented based on their observable types.*

Proof Assume there are two observable consumer types, θ_L and θ_H where $\theta_L < \theta_H$. Denote the service fee charged to low observable types as $\tau_L = \theta_L t + T$ and to high observable types $\tau_H = \theta_H t + T$. The optimal nondiscriminatory service fee is T^0 and the optimal discriminatory services fees to low and high types are $\tau_L^* = \theta_L t^* + T^*$ and $\tau_H^* = \theta_H t^* + T^*$. The monopoly profits can be written as $\pi(\tau_L, \tau_H) = \pi_L(\tau_L) + \pi_H(\tau_H) = (\tau_L - c)q_L(\tau_L) + (\tau_H - c)q_H(\tau_H)$ where $q_L(\tau_L) = \int_{\hat{\mu}(\tau_L,\theta_L)}^{\mu_H} f(\theta_L, \mu)d\mu$ and $q_H(\tau_H) = \int_{\hat{\mu}(\tau_H,\theta_H)}^{\mu_H} f(\theta_H, \mu)d\mu$. Then, to evaluate the welfare effect of allowing the service provider to charge a proportional fee, the monopolist is initially not allowed to charge a proportional service fee and hence charges the nondiscriminatory fee T^0 to both consumer types. Then, the constraint on t is gradually relaxed up to the point where the monopolist is free to set the optimal value t^* (and corresponding T^*). This problem is equivalent to relaxing the constraint for a monopolist that directly chooses τ_L and τ_H (rather than t and T) under the restriction that $\tau_H - \tau_L \leq r$, which is precisely the problem Aguirre, Cowan and Vickers (2010) consider to evaluate the impact of third-degree price discrimination on welfare. They evaluate the impact of gradually raising r from 0 to $r^* \equiv \tau_H^* - \tau_H^*$ which is equivalent to gradually raising t in the present setting, up to a scalar $(\theta_H - \theta_L)$, which is irrelevant for the results. QED

Aguirre, Cowan and Vickers (2010) impose three important assumptions to evaluate the welfare effect, which translate to the present setting as follows: (i) profits in each market segment are strictly concave in the service fee, i.e. $\partial^2\pi_I/\partial\tau_I^2 = \partial^2\pi_I/\partial T^2 < 0$ for $I = L, H$, which is more strict than the required second-order restriction on T in the present setting that total profits need to be concave, (ii) all markets are served under the nondiscriminatory price, i.e. $\forall\theta: \hat{\mu}(T, t, \theta) < \mu_H$, which again might be violated in the present setting. When allowing for proportional fee pricing also expands the market, the welfare effect is more likely to be positive, and (iii) the ratio $(\partial W_I/\partial T)/(\partial^2\pi_I/\partial T^2)$ is strictly increasing in T, which is referred to as the increasing ratio condition. This is the key condition in Aguirre, Cowan and Vickers (2010) which makes the welfare analysis tractable and the authors argue that it is satisfied for a broad range of commonly used distributions to model demand.

In addition, define $\partial^2 q_I / \partial T^2$ as the curvature of direct demand and $\partial^2 T_I(q_I)/\partial q_I^2$ as the curvature of inverse demand, where $T_I(q_I)$ follows from inverting demand in each market segment with respect to T. Then, under assumptions (i) - (iii), the welfare results of Aguirre, Cowan and Vickers (2010) can be translated to the present setting as summarized in proposition 3.2.

Proposition 3.2 (propositions 1-3 in Aguirre, Cowan and Vickers (2010)) *Allowing a monopoly service provider to charge a fee proportional to the value of observable types* (θ_L, θ_H) *increases welfare when inverse demand in the low-type market is more convex than in the high-type market and the spread between high and low types* $(\theta_H - \theta_L)$ *is sufficiently small, and it reduces welfare when direct demand is more convex in the high-type market. If direct demand is more convex in the low-type market at the nondiscriminatory fee and inverse demand is at least as convex in the high-type market than in the low-type market at the discriminatory service fees, then welfare initially rises as the proportional fee increases and then falls.*

The results of Aguirre, Cowan and Vickers (2010) can readily be generalized to multiple consumer types, as formalized by Schmalensee (1981). In the setting of proportional service fee pricing, Wang and Wright (2014) show that this also true in their model for a competitive multiple goods market with proportional consumer demands. Furthermore, they generalize some of the results for a broader class of distributions that those that fall under the increasing ratio condition. In general, however, absent of restrictions on the joint distribution of observable and unobservable types (except of course the second-order restrictions discussed in the previous section) the welfare effects in proposition 3.2 do not necessarily carry through for multiple (or a continuum) of observable types. This because a service provider that has only two strategic decision variables (T and t) to serve more than two market segments is more restricted than a monopolist that third-degree price discriminates, i.e. charges a specific uniform price to each market segment. I am currently working on more general conditions to evaluate the welfare effect of allowing for proportional fee pricing. I expect that this additional restriction will have a moderating effect on the welfare results. That is, when third-degree price discrimination is harmful (beneficial), proportional fee pricing will be less harmful (beneficial), but further research is required to formalize this claim.

5 Discussion

This section discusses three important directions in which the stylized model analyzed in the previous sections could be extended to make it more broadly applicable.

5.1 Imperfect competition among service providers

The analysis in this paper focused on the conditions that make it profitable for a monopolist to make use of a proportional fee as a pricing instrument. In the presence of competition, however, this choice is more restricted given that service providers might steal business from one another by charging a flat fee instead of a proportional fee. More specifically, Veiga and Weyl (2014b) demonstrate that the usage of product characteristics to select valuable consumers into the market (and hence the described selection and sorting effect induced by the usage of such a characteristic) quickly disappears when the market converges towards perfect competition. In the present setting this implies that the market would converge to efficiency given that flat fee marginal cost pricing is the social first-best. Nevertheless, proportional fee pricing is prevalent in practice, even in markets that are seemingly competitive (e.g. online marketplaces, real estate brokerage markets). So, there must be institutional features in these markets that somehow prevent the market to converge towards the perfectly competitive equilibrium. This could be the presence of fixed costs or the incentives to provide higher quality services when proportional fees are available, issues worth further investigation.

5.2 Ramsey pricing

Not only private service providers commonly make use of proportional pricing instruments, but also tax authorities prevalently use ad-valorem taxes to raise tax revenues. Analyzing the Ramsey pricing problem could contribute to the literature on optimal indirect and indirect taxation (see Keen (1998) and Piketty and Saez (2014), respectively, for surveys) and reevaluate some of the issues in the presence of flexible multidimensional heterogeneities of market participants.

5.3 Imperfect competition in the input market and two-sidedness

The examples used to illustrate the intuition of the model assumed that one side of the market was perfectly competitive (firms and sellers in the labor and multiple goods market example, respectively). This conveniently allowed me to analyze the optimal pricing behavior of the service provider in a “one-sided” setting. Of course, in practice the input providers might also possess bargaining power or market power in determining the value of the observable characteristic proportional to which the service provider charges its fee (e.g. wages or sales prices). Allowing for this would imply that the chosen service fee also affects the optimal behavior of the input providers, which in turn affects the utility of consumers. To account for these issues, the model has to analyzed in a “two-sided” setting. Loertscher and Niedermayer (2013) explore the issues in a model with flexible bargaining among buyers and sellers in a setting where the service provider can implement an incentive compatible mechanism by which all relevant heterogeneities on both sides of the market become revealed. Shy and Wang (2011) evaluate a single good market in which the seller and the service provider both possess market power and consumers are heterogeneous in a single dimension. It would be interesting the extend the present model to further explore these issues in a setting where part of the relevant heterogeneities remain unobservable to the service provider on both sides of the market.

6 Conclusions

This chapter presented a monopoly pricing model in which a service provider attracts consumers allowed to be heterogeneous in two dimensions. One dimension of consumer types always remains private information. The other consumer type, however, is assumed to become revealed to the monopolist once the service is provided and a fee can be charged proportional to its revealed value on top of a flat service fee.

It is shown that the service provider only makes use of a proportional service fee if its use induces advantageous selection of consumers into the market. In addition, the monopolist exclusively uses a proportional fee and no flat fee when the advantageous selection effect outweighs the adverse sorting effect at the margin, which is inherent to the use of this fee type. In terms of welfare, it is shown that a Pigouvian planner never charges a proportional service fee because it has an inefficient misallocation effect, familiar from the third degree price-discrimination literature. Furthermore, it is demonstrated that allowing a monopolist to use of a proportional fee has identical welfare effects as allowing for third-degree price discrimination when there are only two observable consumer types. This result does not generalize, however, two multiple consumer types and further research is required to explore this issue.

Chapter 4

Competitive Service Fees, Free Entry and Social Efficiency in Real Estate Brokerage Markets[1]

1 Introduction

This chapter presents a model of imperfect competition among brokers that operate in a market for real estate and charge a service fee to sellers that possibly consists of flat and proportional component, as in the previous chapter. The model is more specific, however, than the one presented in chapter 3 in the sense that it only allows for a single source of heterogeneity in buyer valuations and seller reservation prices, thus the selection and sorting effects described above do not appear here. Apart from allowing for broker competition and proportional fee pricing, the model presented in this chapter also differs from to the ones presented in the first two chapters in that it assumes an efficient matching technology. This implies that the network externalities that emerge from the imperfect matching process captured by the matching elasticities will play no role. While these externalities are important for large decentralized matching technologies, as the one offered by the listing platform analyzed in chapter 2, they are

[1] This chapter is based on joint work with Roel Helgers, Maarten Goos and Erik Buyst. Roel Helgers provided great help in constructing the tables and figures reported in this chapter, for which many thanks. Of course, all errors are my own responsibility and mine to defend.

expected to be of less importance for matchmakers that offer individual matching services like real estate brokers and therefore are not taken up in the analysis. In contrast, the externalities that arise from the bargaining process discussed in chapter 2, do will play an important role. In addition, similar to chapter 2, the presented model is also taken to the data to evaluate market efficiency in the Belgian real estate brokerage market. The used data are richer that those in chapter 2 and therefore more refined estimates for the model parameters can be provided.

The motivation for the analysis in this chapter, as already discussed in the general introduction of this this dissertation, is that the competitive environment of brokers that operate in real estate markets has drastically been changing over the past two decades. Before, throughout most of the 20^{th} century, commission rates charged by brokers have been known to be very rigid, suggesting a lack of competition among brokers in pricing there services. Since the rise of the internet, however, the traditional information systems that upheld this apparent collusive behavior have been severely under pressure. The novel information technologies make brokers rely less heavily on their colleagues to establish valuable real estate transactions which has led brokers to deviate from offering the traditional service packages and from the conventional fixed commission rates. The USDOJ-FTC (2007) present a detailed report on this transition for the US brokerage industry. Supporting empirical evidence for the increased variation in commission rates in various local US markets is given, for example, by Sirmans and Turnbull (1997), Schnare and Kulick (2009) and Wiley, Benefield and Allen (2012).

A natural question that arises is how the intensified competition among brokers in pricing their services affects the market outcomes. This question is particularly relevant to investigate because the traditional “fixed” commission rates are known to entail significant social losses. More specifically, in their seminal contribution, Hsieh and Moretti (2003) demonstrate that fixed commission rates combined with limited entry constraints for new brokers to enter local housing markets can be an important source of inefficiencies. Under free entry, an excessive amount of brokers enter in local markets with relatively high average prices of housing because more revenues can be extracted there by the proportional nature of the commission rate. In these relatively expensive markets, brokers inefficiently compete for transactions and a significant amount physical and human resources is invested which produces little social value in return. Hsieh and Moretti (2003) estimate a social loss due to excessive broker entry of billions of dollars across the US for the period 1980-1990, up to 50% of total industry revenue in their most pessimistic estimates.

This chapter aims to contribute by addressing the question how market efficiency is affected when brokers do compete in setting commission rates in real estate markets. To do this, the analysis is built up as follows. Section 2 presents the model of imperfect broker competition. Following Weyl and Fabinger (2013), it is shown that the degree of competition among brokers can be captured by a single “competitive conduct” parameter on the unit interval, where zero corresponds to Bertrand competition and one to brokers colluding on the monopoly service fee. In addition, the model allows for fixed entry costs and free broker entry, such that the distortions that might arise from free entry emphasized by Hsieh and Moretti (2003) can be evaluated.

Section 3 presents the theoretical results. It is shown that neither broker collusion (monopoly) nor perfect broker competition (Bertrand) can be socially efficient. This because the negative cross-side externalities that arises from the bargaining process are not properly internalized in the service fees under perfect competition. Under monopoly, these externalities do are properly internalized, but on top of this there is the classic Cournot distortion, such that the monopoly service fee is always too high from a social point of view, consistent with the findings in chapter 2. Therefore, an intermediate degree of broker competition is socially optimal.

The crucial feature of the model that drives this result is that there is uncertainty about the trading partner buyers and sellers will eventually meet when they enter the market. In this case it is socially efficient (within homogeneous local submarkets) to exclude some buyers with a low willingness to pay and sellers with high reservation prices from the market because their participation decision causes a negative cross-side externality on the more efficient high value buyers and low reservation price sellers that participate through the bargaining process over the transaction price. This externality should be internalized in the service fee charged by brokers, justifying a positive markup over marginal costs. This result is consistent with the findings of Mahoney and Weyl (2014), who demonstrate a similar inverse u-shaped relationship exists in selection markets characterized by advantageous selection. The present market can also be interpreted as being characterized by advantageous selection (although different than described in chapter 3) in the sense that high willingness to pay buyers and low reservation price sellers are also the ones that bring most value to market through the established transactions.

In addition, consistent with Mankiw and Whinston (1986), it is shown that in the presence of fixed costs, free broker entry is always excessive. Both findings combined, that marginal cost pricing is not efficient and that entry is always excessive, has important implications for the effectiveness of different policy instruments that can be used should a social planner want to regulate the market to establish the social optimum. When the observed service fee is *below* the socially optimal level, regulating the service fee brokers are allowed to charge will result in a conflict of interest. Raising the fee will bring it closer to its desired level, but it will also worsen the entry distortion because a higher markup for a given fixed cost will incentivize more brokers to enter the market. In this case, it is preferable the regulate broker entry if possible, given that restricting the number of brokers allowed to operate the market will both raise the service fee and mitigate the entry distortion. In contrast, when the observed service fee is *above* the socially optimal level, the opposite policy recommendation holds. Restricting entry will mitigate the entry distortion, but will also undesirably further raise the service fee. In contrast, regulating the service fee in this case can again mitigate both distortions at the same time, given that for a lower service fee some brokers will be forced to exit the market.

Section 4 demonstrates how the model parameters can be identified when data on broker service fees, market shares and the distribution of sales prices of real estate are observable. Section 5 presents the available data for the present study, shows how some of the data imperfections can be resolved and reports the parameter estimates. Section 6 presents welfare counterfactuals of the social first-best, the outcomes when a social planner would regulate broker entry and when a planner would directly regulate the service fees. Given that in the observed equilibrium the average service fee is below the social optimum, entry regulation is predicted to yield a welfare gain of about 20%. In contrast, regulating the service fee, neglecting the entry effect, would result is a welfare *loss* of about 40%. These results illustrate the importance of making the proper choice of which policy instrument to use should a policymaker aspire to intervene in a real estate brokerage market.

In the literature, there is vast body of research that investigates issues concerning the US brokerage industry. Benjamin, Jud and Sirmans (2000) and Zietz and Sirmans (2011) provide excellent surveys on the topic. Related to market efficiency, seminal contributions that point out conditions under which fixed commission rates can be socially wasteful are Yinger (1981), Crockett (1982), Miceli (1992) and Hsieh and Moretti (2003), where the latter is closest related to the present setting given the focus on excessive entry. Other recent work that builds on Hsieh and Moretti (2003) is that of Han and Hong (2011), who extend the model with generalized costs and test for cost inefficiencies across US local markets, and Jia and Pathak (2012), who exploit the dynamics of entry in Greater Boston's brokerage industry to evaluate market efficiency. Both papers maintain the assumption that commission rates are fixed and they report findings in line with Hsieh and Moretti (2003).

Closest related theoretical contributions on broker competition in setting commission rates are those of Yavas (2001) and Loertscher and Niedermayer (2013). Yavas (2001) demonstrates in a homogeneous buyer-seller-broker framework that in the presence of fixed costs, the only unique Nash equilibrium is the monopoly outcome, suggesting that a competitive equilibrium is therefore infeasible in real estate brokerage markets. It can be argued, however, that this result no longer holds as soon as brokerage services are somehow differentiated from the point of view of buyers and sellers, for example, by their location. In principle, any equilibrium in between Bertrand and monopoly is then feasible, depending on the degree of residual market power of individual brokers, as it is modeled is the present study. The contribution of Loertscher and Niedermayer (2013) was already discussed in previous chapters. Relevant for the present setting is that they do not conduct the free entry analysis, which is the precisely emphasis of the present chapter.[2]

As mentioned above, empirical contributions that support the increased variation in commission rates across the US are Sirmans and Turnbull (1997), Schnare and Kulick (2009) and Wiley, Benefield and Allen (2012). They explore the role of increased price competition among brokers to explain this phenomenon, but none of these studies structurally estimates the impact of price competition on market efficiency.

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[2] Other related theories of broker competition are presented by Bruce and Santore (2006) and Miceli, Pancak and Sirmans (2007). Again, none of these contributions evaluates market efficiency under free broker entry as the present chapter does.

Finally, this chapter also contributes to the theoretical (e.g. Mankiw and Whinston (1986)) and empirical (e.g. Bresnahan and Reiss (1991) and Berry and Waldfogel (1999)) work that investigates market efficiency under free entry for homogeneous goods oligopolies, by showing that in markets where marginal cost pricing is not socially optimal, the incentives of a social planner that aims to mitigate price distortions are not necessarily aligned with those of a social planner that aims to minimize social waste that results from free entry.

2 Model

Consider a four-stage static model of symmetric imperfect competition among brokers who offer a service of matching buyers and sellers in a market for a homogeneous real estate good. The timing of the model can be summarized as follows:

Stage 1: N brokers (out of an unrestricted amount) enter the market.

Stage 2: Participating brokers simultaneously announce the brokerage fees charged to sellers and buyers in return for their services.

Stage 3: N^S sellers (out of a potential mass S) and N^B buyers (out of a potential mass B) enter the market through one of the brokers.

Stage 4: M matches occur through the brokerage industry and generated transaction surpluses are divided among the three parties of interest.

Assume that brokers, sellers and buyers are risk-neutral and that sellers and buyers have unit supply and demand, respectively. Sellers are heterogeneous in their reservation price of providing the good to the market, denoted by s and assumed smoothly distributed by $F^S(.)$ with density $f^S(.)$ on $[s^L, s^H]$ with $s^H > s^L$. Similarly, buyers are heterogeneous in their valuation for the good, denoted by b and assumed smoothly distributed by $F^B(.)$ with density $f^B(.)$ on $[b^L, b^H]$ with $b^H > b^L$. The distributions of seller reservation prices and buyer valuations are public information. Individual seller reservation prices and buyer valuations, however, are private information up to the point where sellers and buyers decide on participation (stage 3) and they become revealed once a buyer is matched to a seller (stage 4). The outside option of not participating in the market through one of the brokers is normalized to zero for both sellers and buyers.

In addition, assume that all agents have rational expectations about the events that occur throughout the different stages of the model. The remainder of this section further specifies the exact events that occur in each stage, starting with the last stage of the model, and specifies the welfare criteria that will be used to evaluate efficiency of the private market outcomes.

2.1 Individual transaction valuations (stage 4)

When sellers participate in the market by hiring a broker they are charged a fee that only has to be paid conditional on being matched. The fee possibly consists of a flat component p and a commission rate t charged proportional to the sales price of the property. The individual transaction value of a seller type s can hence be written as:

$$(1-t)\rho - p - s \tag{1}$$

where ρ denotes the transaction price. Buyers are not charged directly for the broker service and the individual transaction value of a buyer type b can therefore be written as:

$$b - \rho \tag{2}$$

The fee charged to the seller, however, is possibly passed through in the bargain over the sales price between the buyer and the seller. More specifically, assume the transaction price is chosen to maximize an asymmetric Nash bargain:

$$\max_{\rho}(b-\rho)^{1-\beta}\big((1-t)\rho - p - s\big)^{\beta} \tag{3}$$

where $\beta \in [0,1]$ denotes the bargaining weight of sellers and hence $1-\beta$ is the bargaining weight of buyers.[3] This yields the following expression for the transaction price:

$$\rho(b,s) = \beta b + (1-\beta)\frac{p+s}{1-t} \tag{4}$$

[3] Note that in practice, the broker, rather than the seller, usually bargains over the transaction price with potential buyers (or buyer brokers) in most real estate markets. However, a seller-broker (buyer-broker) contract typically also explicitly specifies that the broker should represent the best interest of the seller (buyer) in this process, which is assumed to be case here. More generally, this chapter ignores any potential principle-agent problems concerning the seller-broker or buyer-broker relationship. See Benjamin, Jud and Sirmans (2000) and Zietz and Sirmans (2011) for reviews of the existing literature on these type of issues.

The assumptions on the bargaining process have two convenient implications for the purpose of our analysis. On the one hand, Nash bargaining is efficient in the sense that any match for which the buyer valuation is sufficiently high to cover the seller reservation price and broker fees will be established. In alternative price determination games there might be additional distortions that arise from seller and/or buyer market power or informational imperfections[4]. Given the focus of this paper on the distortions that possibly arise from broker market power, however, we prefer to exclude any additional potential inefficiencies. On the other hand, by assuming that sales prices are determined at the individual transaction level, rather than through a competitive market clearing mechanism (which would also exclude the aforementioned additional distortions), implies *ex post* sales price dispersion for homogeneous real estate goods. In the empirical part of this paper, it is precisely the residual variation in sales prices (after controlling for observable real estate characteristics) that will be used to identify the buyer demand and seller supply parameters of the model.

2.2 Buyer and seller participation (stage 3)

Assume that the service offered by brokers is possibly perceived as differentiated across buyers and across sellers, for example, by the different locations of the brokers. Service differentiation is restricted, however, by the assumption that in equilibrium a symmetric and representative set of buyers and sellers is attracted by each broker. More specifically, market

[4] See, for example, Burdett and Mortenson (1998).

supply of sellers is equal to $N^S = \sum_{i=1}^{N} n_i^S$ where n_i^S is the number of sellers attracted by broker i, which is assumed to be the same across brokers: $n_1^S = \ldots = n_N^S = N^S/N \equiv n^S$. Similarly, market demand for buyers is equal to $N^B = \sum_{i=1}^{N} n_i^B$ where n_i^B is the number of buyers attracted by broker i again assuming symmetry across brokers: $n_1^B = \ldots = n_N^B = N^B/N \equiv n^B$. In addition, assume that the matching technology offered by the brokers is efficient and random. That is, the amount of matches established by every broker is equal to $\min[n^B, n^S]$, the match probability of sellers is $\min[n^B, n^S]/n^S \equiv m^S$ and the match probability of buyers is $\min[n^B, n^S]/n^B \equiv m^B$. By broker symmetry, it follows that the equilibrium amount of matches that occur through the brokerage market is equal to $M = \min[N^B, N^S]$. In what follows, broker subscripts are omitted to minimize the notational burden in the exposition of the model.

Expected seller and buyer utility of participating through the brokerage market can be written as:

$$u^S = \left((1-t)\rho(\bar{b}, s) - p - s\right)m^S = \beta\left((1-t)\bar{b} - p - s\right)m^S \quad (5)$$

$$u^B = (b - \rho(b, \bar{s}))m^B = (1-\beta)\left(b - \frac{p+\bar{s}}{1-t}\right)m^B \quad (6)$$

where $\bar{b}$ denotes the expected buyer valuation for the good and $\bar{s}$ the expected seller reservation price, respectively:

$$\bar{b} = \frac{B}{N^B}\int_0^{N^B/B} F^{B^{-1}}(1-x)dx \quad (7)$$

$$\bar{s} = \frac{S}{N^S}\int_0^{N^S/S} F^{S^{-1}}(x)dx \tag{8}$$

Sellers participate when $u^S \geq 0 \Leftrightarrow s \leq (1-t)\bar{b} - p \equiv \tilde{s}$, where $\tilde{s}$ denotes the reservation price of the marginal seller that participates through the brokerage market. Similarly, buyers participate when $u^B \geq 0 \Leftrightarrow b \geq \frac{p+\bar{s}}{1-t} \equiv \tilde{b}$, where $\tilde{b}$ denotes the marginal buyer valuation. Market supply of sellers and market demand for buyers can thus be summarized as:

$$N^S = SF^S(\tilde{s}) \tag{9}$$

$$N^B = B\left(1 - F^B\left(\tilde{b}\right)\right) \tag{10}$$

Note from expression (9) that market supply of sellers not only depends on the service fees p and t charged by brokers, but also depends on the amount of buyers that participate, through the expected buyer valuation $\bar{b}$. Furthermore, $\bar{b}$ depends negatively on N^B, as is clear from expression (7), and hence seller supply is characterized by a negative externality induced by the participation decision of buyers. This because high value buyers enter the market first and because sellers do not know to which buyer they will be matched when they decide on participation (matching is random). This implies that increased buyer participation lowers the sales price sellers expect to receive, which in turn lowers seller supply. Similarly, expression (10) shows that market demand for buyers is characterized by a negative externality induced by the participation decision of sellers, through the expected seller reservation price $\bar{s}$. Low reservation price sellers enter the market first and hence increased seller participation raises the sales price buyers expect to pay, which in turn lowers buyer demand. These externalities, which exist by the presence of transferable utility among sellers and buyers in the model, will prove to be important for the results reported below.[5]

Using the definitions of $\tilde{s}$ and $\tilde{b}$ allows us to write the market clearing flat fee p and commission rate t as a function of marginal and average preference values of sellers and buyers:

$$p = \frac{\tilde{b}\tilde{s} - \bar{b}\bar{s}}{\bar{b} - \tilde{b}} \tag{11}$$

$$1 - t = \frac{\tilde{s} - \bar{s}}{\bar{b} - \tilde{b}} \tag{12}$$

Expressions (11) and (12) can be interpreted as a system of inverse demand equations, in which $\tilde{b} = {F^B}^{-1}(1 - N^B/B)$ and $\tilde{s} = {F^S}^{-1}(N^S/S)$, as follows from (9) and (10), and $\bar{b}$ and $\bar{s}$ are given by expressions (7) and (8). In what follows, it will be assumed that any equilibrium market allocation

[5] Note that there is an additional channel through which externalities can result from the participation decision of users on either side. As is clear from the expressions (5) and (6) for expected seller and buyer utilities, respectively, the match probabilities of users on both sides, $m^S = \min[N^B, N^S]/N^S$ and $m^B = \min[N^B, N^S]/N^B$, also depend on the participation decision of users on both sides. The assumption that the matching technology is efficient, however, will imply that brokers always balance the market, as formalized below. This in turn implies that the match probabilities of both buyers and sellers are equal to 1 in equilibrium and that the internalization of these externalities will not explicitly appear in the optimal pricing conditions of brokers (nor in those of the social planner). Allowing for additional frictions in the matching process would deflect us from the main focus of this paper, which is to investigate the implications of imperfect broker competition in pricing their services on market efficiency in the long-run, a focus for which the efficient matching assumption seems reasonable. That is, one could consider our model as reduced form to analyzing the market outcome in a dynamic model at the long-run steady state equilibrium, where we are not directly concerned with the cyclical fluctuations around this steady state. See, Goos, Van Cayseele and Willekens (2014) for a more general treatment of the implications of short-run matching frictions on optimal platform pricing.

N^B, N^S is uniquely established through the two market clearing values of the pricing instruments p and t that follow from (11) and (12). In other words, we assume that the two available pricing instruments suffice to resolve the coordination problem faced by the brokers to attract two distinct user groups in the presence of indirect network externalities.[6]

2.3 Imperfect broker competition (stage 2) and social first-best

Expected broker profits can be written as:

$$\pi = (AR - MC) \min[n^B, n^S] - FC \tag{13}$$

where $MC \geq 0$ denotes a constant per-match cost incurred by each broker when matching buyers and sellers, $FC \geq 0$ denotes a fixed cost incurred by

[6] The described coordination problem, also referred to as the chicken-and-egg problem, is well-known from the two-sided markets literature. In that literature various solutions were proposed to resolve the problem. For example, Caillaud and Jullien (2001, 2003) introduce the concept of "favorable beliefs", Weyl (2010) introduces the concept of "insulating tariffs" for monopoly and White and Weyl (2012) of "insulated equilibrium" for platform competition and Filistrucchi and Klein (2013) introduce restrictions on the magnitude of network effects to guaranty existence and uniqueness in differentiated Bertrand equilibrium. None of these concepts are directly applicable to the present setting, however, by our assumption on transferable user utilities. We view exploring this issue as an important direction for future research, however, beyond the scope of this paper. One argument in favor of our simplifying assumption that the coordination problem is always resolved is that it is supported by the data used in the empirical part of this paper, which show that none of the investigated local markets unravels to the non-participation equilibrium, even though only a flat and proportional fee charged to sellers is used as a pricing instrument by brokers. In a sense this is not surprising, given that it is precisely an important part of the "job" of real estate brokers to deal with this coordination problem. Furthermore, brokers can credibly commit to buyers and sellers to resolve the problem to their best effort, given that payments to the broker only occur when a transaction is actually established. By this logic, the coordination problem is less of an issue in markets with transferable utilities and conditional payments compared to the classic two-markets examples where the platform has no direct control over the interactions between attracted user groups, like payment cards or newspapers.

each broker to operate in the market, independent of the amount of matches established, and AR is defined as expected per-match marginal revenue:

$$AR \equiv p + t\bar{\rho} \tag{14}$$

in which $\bar{\rho}$ denotes the expected transaction price of transactions that occur through the brokerage market, which can be written as:

$$\bar{\rho} = \beta\bar{b} + (1-\beta)\tilde{b} \tag{15}$$

Note that by using expressions (11), (12) and (15), average per-match revenue can be written as a function marginal and average user types, which in turn only depend on the amount of buyers and sellers attracted in the brokerage market and not on the specific pricing instruments used by the brokers:

$$AR = \beta\left(\bar{b} - \tilde{s}\right) + (1-\beta)\left(\tilde{b} - \bar{s}\right) \tag{16}$$

To model symmetric imperfect competition among brokers in providing their service to the market, we follow the approach proposed by Weyl and Fabinger (2013) by which the degree of imperfect competition can be captured by a single "conduct parameter", extended to our setup where competing brokers attract and efficiently match two distinct user groups. To do so, we first impose the assumption that competitive interactions among brokers (and the distributions of buyer and seller types) are restricted such that average per-match revenue for individual brokers is strictly decreasing in the amount of users attracted on both sides of the market, i.e. $dAR/dn^I < 0$ for $I = B, S$. This implies that individual broker profits, given by expression (13), are strictly decreasing in the amount of users on one side if the attracted amount of users on that side exceeds the amount of users attracted on the other side, i.e. $d\pi/dn^I < 0$ if $n^I > n^J$ for $I \neq J$. This in turn implies that any profit maximizing equilibrium must always be balanced, i.e. $n^S = n^B = n$ or, equivalently, $N^S = N^B = M$. If not, brokers can always raise profits by lowering the amount of users on the long side of the market. This result directly follows from the assumption that the matching technology available to brokers is efficient. This conveniently allows us to convert the problem of brokers competing to attract users on two distinct sides into a problem where the brokers compete in a single quantity (n) by using one of the available pricing instruments (e.g. p). The other available pricing instrument (e.g. t) is “mechanically” adjusted to ensure the balanced market condition holds and therefore no longer needs to be considered as a strategic variable.

Now, following Weyl and Fabinger (2013) (who themselves build on earlier contributions in the literature by Bresnahan (1989) and Genesove and Mullin (1998)), instead of explicitly modeling the interactions among competing brokers, we assume that in any imperfectly competitive equilibrium the elasticity-adjusted Lerner index is set equal to a conduct parameter θ, which in our model satisfies:

$$\frac{AR - MC}{AR}\left(-\frac{dM}{dAR}\frac{AR}{M}\right) = \theta \qquad (17)$$

where $\theta \in [0,1]$ when the broker services are substitutes, which we assume to be the case throughout this paper. As formalized by Weyl and Fabinger (2013), this framework nests a broad range of imperfect competition models, among which monopoly or cartel ($\theta = 1$), Bertrand ($\theta = 0$), Cournot ($\theta = 1/N$), Bresnahan (1989)'s constant conjectural variations model ($\theta = (1+R)/N$ where $dM/dn = 1+R$), symmetrically differentiated Nash-in-prices and monopolistic competition. For the latter two models θ is not a constant. We do not derive explicit conditions for these models for our setup (where we would have to account for the "mechanical" adjustment of t), however, given that none of the results in the next section hinge on the specific underlying model of imperfect competition. The only thing that matters, is that any model outcome on the continuum between monopoly and Bertrand is a feasible imperfect competition equilibrium, which we assume to be case.

To evaluate market efficiency in the second stage of the model, the private market equilibrium it is compared to the outcome determined a Pigouvian planner that optimally chooses the number sellers N^S and buyers N^B attracted in the brokerage industry to maximize total social value, taking the amount of brokers that operate the market as given. Total social value generated in the market is equal to the sum of total industry profits $\Pi \equiv \pi N$ and total consumer surplus CS, defined as the sum of total buyer and seller surplus, which can be written as:

$$CS = \left(\beta\left(\bar{b} - \tilde{b}\right) + (1-\beta)(\tilde{s} - \bar{s})\right)\min[N^B, N^S] \tag{18}$$

By combining equations (13), (16) and (18), total social value W simplifies to:

$$W = \left(\bar{b} - \bar{s} - MC\right)\min[N^B, N^S] - FC * N \tag{19}$$

It can easily be shown that $\bar{b} - \bar{s}$ is strictly decreasing in N^B and N^S, which implies that the Pigouvian planner always balances the market, i.e. $N^B = N^S = M$, because welfare is strictly decreasing in participation on the long side of the market. This again conveniently allows us to simplify the social optimization problem to a problem with a single strategic decision variable, in this case M.

2.4 Free broker entry (stage 1) and social second-best

In the first stage of the model brokers can freely enter the market and they will do so as long as profits of the marginal entrant are weakly positive. Ignoring the integer constraint on the number of brokers (in the empirical part of this paper we do account for this) and by our assumptions on broker symmetry this implies that individual broker profits must be equal to zero in the free entry equilibrium, i.e. $\pi = 0$.

The private outcome of the first stage of the model is compared to that of a social planner who optimally chooses the amount of brokers that operate the market, taking private broker once they entered the market as given. That is, the planner maximizes W, given by expression (19) in which $N^B = N^S = nN$, by optimally choosing N, taking into account that the amount of buyers and sellers attracted by individual brokers n is affected by N through the private first-order conditions in the second stage of the model. This second-best social optimization problem is the one considered by Mankiw and Whinston (1986) to evaluate the distortions that can arise from unrestricted entry in markets characterized by the presence of fixed costs. It is particularly relevant to analyze this specific welfare criterion in our model, given that Hsieh and Moretti (2003) show in a model with fixed commission rates that the presence of fixed costs combined with free broker entry can result in significant social waste due to excessive entry. We reevaluate this issue in our setting with imperfectly competitive service fees.

3 Analysis

3.1 Private market equilibrium (stage 2) and the first-best social optimum

Proposition 4.1 summarizes the private market equilibrium when an exogenous amount N of symmetric brokers operate the market. The result follows from equating N^S and N^B to M in expression (16) for average per-match revenue, differentiating with respect to M and substituting the solution in the imperfect competition equation (17).

Proposition 4.1 *Optimal private broker behavior implies that the equilibrium amount of matches established through the brokerage market* M *satisfies:*

$$AR - MC = \theta(MS + ET) \tag{20}$$

where MS *denotes marginal consumer surplus, defined as* dCS/dM, *which can be written as:*

$$MS = \beta \frac{F^S(\tilde{s})}{f^S(\tilde{s})} + (1-\beta)\frac{1 - F^B(\tilde{b})}{f^B(\tilde{b})} \tag{21}$$

and ET *refers to an "externality tax", raised to internalize the cross-side participation externalities in buyer demand and seller supply, which can be written as:*

$$ET = \beta(\bar{b} - \tilde{b}) + (1-\beta)(\tilde{s} - \bar{s}) \tag{22}$$

Expression (20) shows that the markup of average per-match revenue over per-match marginal cost is increasing in the conduct parameter θ, ranging from zero under Bertrand competition ($\theta = 0$) to $MS + ET$, which is the monopoly markup ($\theta = 1$). The first term, MS, denotes marginal consumer surplus, which in a standard monopoly model is equal to the inverse hazard rate (or semi-elasticity) of demand and coincides with the classic Cournot distortion. In the present setting, MS is equal to the weighted sum of inverse hazard rates of seller supply and buyer demand, where the weights are equal to the bargaining weight of users on these respective sides. This is intuitive, if one side possesses no bargaining power in determining property sales prices, users on that side capture no surplus from transactions and hence no surplus can be extracted by brokers from that side, independent of the elasticity of demand (supply) on that side.

The second term, ET, refers to the 'externality tax' raised by brokers to internalize the negative externality that the participation decision of marginal participants on either side causes on expected utility of cross-side participants. From expression (22) it is clear that the magnitude of the tax depends on the spread between average and marginal user types on both sides or, in other words, on the degree of heterogeneity in user types. For example, sellers care about the expected buyer valuation when they enter the market. When buyers are homogeneous in there valuation, sellers are indifferent to which buyer they will be matched and the participation decision of the marginal buyer causes no externalities. In this case, $\bar{b} = \tilde{b}$ and the first term in ET disappears because there is no externalities for brokers to internalize on the buyer side. In contrast, when dispersion in buyer valuations is large, the spread between the marginal and average buyer valuation will be large and that marginal buyer entails a large externality. The tax raised to internalize this externality is precisely the spread between the average and marginal buyer valuation, weighted by the bargaining strength of sellers. Similarly, the tax to internalize the externality on the seller side is equal to spread between the marginal and average seller (where the former has a higher reservation price than the latter which is disliked by buyers), weighted by the measure of buyer bargaining power.

Proposition 4.2 summarizes the first-best social optimum chosen by a Pigouvian planner. The result follows from equating N^S and N^B to M in expression (19) for total social value and rewriting the first-order condition with respect to M. The socially optimal degree of broker competition is derived from equating the private and social first-order conditions.

Proposition 4.2 *At the first-best social optimum, the equilibrium amount of matches established through the brokerage market M^* satisfies:*

$$AR - MC = ET \tag{23}$$

This implies that the socially optimal degree of competition among brokers in a private market satisfies:

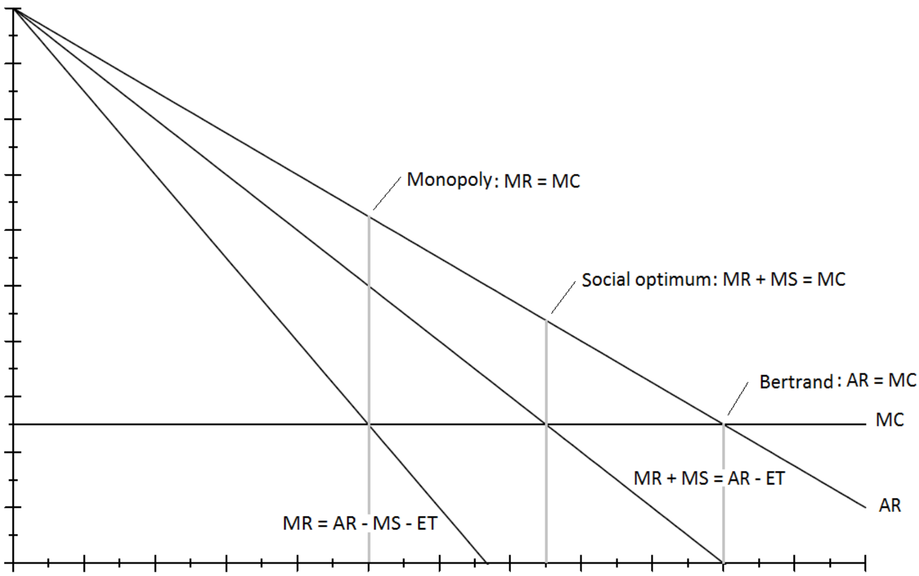
$$\theta^* = \frac{ET}{MS + ET} \tag{24}$$

Expression (23) demonstrates that a Pigouvian planner also taxes the negative externalities induced by the participation decision of users on both sides. Furthermore, it does so exactly to the same extent a monopolist does in the private market, as is clear from expression (20). The externality tax is strictly positive in the presence of heterogeneity in buyer and/or seller types, which implies that Bertrand competition among brokers ($AR = MC$)

is not socially optimal. In this case, broker fees are too low and the equilibrium amount of matches too high compared to the social optimum, because the participations externalities present in the market are not properly internalized. On the other hand, the monopoly outcome can never be efficient, because on top of the externality tax, broker fees are marked up by the weighted Cournot distortion, which results in upward distorted broker fees and hence insufficient participation. So, in a private market there exists an intermediate degree of imperfect competition θ^* which establishes the first-best social optimum. Expression (24) shows that θ^* depends on the magnitude of MS relative to ET. When marginal consumer surplus is small relative to the externality tax, the desired degree of market power is large and vice versa. Which of both measures is largest depends on the underlying distributions of user types and relative bargaining weights, as is clear from expressions (21) and (22).

Note that this result is consistent with the findings of Mahoney and Weyl (2014), who demonstrate a similar inverse u-shaped relationship exists in selection markets characterized by advantageous selection. The present market can also be interpreted as being characterized by advantageous selection in the sense that high willingness to pay buyers and low reservation price sellers are also the ones that bring most value to market through the established transactions. Similar to Mahoney and Weyl (2014), figure 1 summarizes the findings in propositions 4.1 and 4.2 graphically for linear buyer demand and seller supply, illustrating that the social optimum lies in between monopoly and Bertrand and requires a positive wedge between the AR-curve and the MC-curve.

Figure 1: Imperfectly competitive social optimum



3.2 Free broker entry (stage 1) and the second-best social optimum

Under free broker entry, the private market outcome is summarized by the following zero-profit condition:

$$\pi = (AR - MC)\frac{M}{N} - FC = 0 \tag{25}$$

This implies that in free entry equilibrium average revenue is equated to average cost, $AR = AC$, where $AC = MC + (FC * N)/M$. The amount of brokers that enter the market depends on the markup they expect to receive in the second stage, given by expression (20). For example, when brokers collude on charging monopoly service fees, AR and M are independent of the amount of entrants and N is equal to $(AR - MC)M/FC$. At the other extreme, equation (25) shows that Bertrand equilibrium ($AR = MC$) is not feasible in the presence of positive fixed costs, given that a second entrant would not be willing to enter the market, consistent with Yavas (2001). More generally, when market power in the second stage is sufficiently large to cover the fixed cost of at least two entrants, the number of brokers that operate the market follows from the zero-profit condition (25), where AR and M depend on N through the private first-order condition (20). In what follows, we denote the free entry equilibrium number of brokers that operate the market as N^e. This equilibrium is unique when assumptions (a), (b) and (c) specified in proposition 4.3 are satisfied.

Proposition 4.3 summarizes the second-best social optimum of a social planner that optimally chooses the number of brokers that operate the market, taking their private behavior once they have entered the market as given (ignoring the integer constraint on the number of brokers), as in Mankiw and Whinston (1986).

Proposition 4.3 *If for any* N*: (a)* $dM/dN = n + Ndn/dN > 0$*, (b)* $Ndn/dN < 0$ *and (c)* $AR - MC > 0$*, then the free entry equilibrium number of brokers* N^e *strictly exceeds the socially optimal number of brokers, denoted by* N^{**}*.*

At the second-best social optimum, the equilibrium amount of matches established through the brokerage market M^{**} *satisfies:*

$$AR - MC = ET + \frac{FC}{dM/dN} \tag{26}$$

Proof Differentiating expression (19) for total social value, in which $N^S = N^B = nN$, with respect to N yields:

$$\frac{dW}{dN} = \left(\tilde{b} - \tilde{s} - MC\right)\left(n + N\frac{dn}{dN}\right) - FC \tag{27}$$

Equating expression (27) to zero, using the expressions for AR (16) and ET (22), that $n + Ndn/dN = dM/dN$ and rewriting yields expression (26). Note that dM/dN can be written as a function of M by solving the private first-order condition (20) for N as a function of M (the solution is unique by assumption (b)) before differentiating. So, expression (26) can be written solely as a function of M (independent of N) and hence can be solved for the equilibrium amount of matches at the second-best social optimum, which is convenient to interpret the results in comparison to the previous findings.

The excessive entry result follows from adding to and subtracting from expression (27) expression (13) for individual broker profits, in which $n^S = n^B = n$ and $N^S = N^B = nN$, which after rewriting yields:

$$\frac{dW}{dN} = \pi + (AR - MC)N\frac{dn}{dN} - ET\left(n + N\frac{dn}{dN}\right) \tag{28}$$

Expression (28) illustrates the distortions that result from free entry in the private market relative to the social optimum. Under free entry in the private market individual broker profits equate zero ($\pi = 0$), while entry is socially optimal when the impact of the marginal entrant on social welfare is zero ($dW/dN = 0$). So, expression (28) implies that private entry and socially optimal entry coincide when the sum of the second and the third term equals zero. When the sum of these terms is negative, there is excessive entry. This because $d\pi/dN < 0$, so $dW/dN = 0$ only holds when the number of brokers is smaller than under private entry. By assumptions (a)-(c) and the fact that $ET > 0$, the last two term in (28) are strictly negative and hence the private free entry equilibrium is unambiguously characterized by excessive entry. QED

The result that the private free entry equilibrium is always characterized by excessive entry is consistent with the findings of Mankiw and Whinston (1986), who demonstrate under the same set of assumptions (a)-(c) that in standard oligopoly models there is always excessive entry in the presence of fixed costs. The intuition is that private brokers when they enter the market do not internalize a negative externality on the profits earned by incumbent brokers, referred to as the business-stealing effect. That is, when a new broker enters, the market "expands" (assumption (a)) in the sense that more matches will be established through the brokerage market, but if the market expansion is smaller than the individual amount of matches established by the incumbent brokers prior to the entry decision of the marginal entrant, this entrant also "steals business" from the incumbent brokers (assumption (b)). Absent of fixed costs, business-stealing has no social cost, i.e. generated revenues in the market are simply divided by more brokers. In the presence of fixed costs, however, business-stealing implies that investments in fixed costs are "wasted" from a social point of view, given that the same market outcome could also be established by less brokers and hence less investments in fixed costs.

In this light, a brokerage market where commission rates are "fixed", as for the US case analyzed by Hsieh and Moretti (2003), is the worst case scenario. This because the amount of matches that occur through the brokerage market is also fixed and entry of brokers induces only a business-stealing effect and no market expansion effect and hence the social cost from free entry will be maximal. For comparison, one can think of this case as brokers colluding on the monopoly service fee in the present setting, in which case M is also unaffected by N. Compared to this case, increased broker competition is likely to mitigate the problem, given that this implies that additional entrants expand the market. There is a limit to this, however, given that there exists an inverse u-shaped relationship between the degree of broker competition and welfare in the present setting, as formalized above. Furthermore, expression (26) shows that the second-best social planner internalizes the additional externality induced by the entry decision of brokers by setting an even higher markup of average revenue over marginal cost compared to the first-best social optimum, given by expression (23). The divergence between the first-best and the second-best is larger when fixed entry costs are larger and when the market expansion effect ($dM/dN = n + Ndn/dN$) relative to the business-stealing effect (Ndn/dN) is smaller or, in other words, when the social cost induced by the marginal entrant is higher.

The comparison between social first-best (23) and second-best (26) is also instructive about the effectiveness of various policy instruments that could potentially be used to regulate real estate brokerage markets. To see this, note that the first-best social optimum can only be established when fixed entry costs are zero. So, should a policy maker be able to eliminate all fixed operating costs, the first-best could be established by regulating the service fees charged by the brokers in such a way that the degree of broker competition satisfies the socially optimal level $\theta = \theta^*$. If one is not able to influence fixed operating costs, however, if one plans to regulate the service fees in the market, one should also be concerned with the amount of brokers that enter the market.

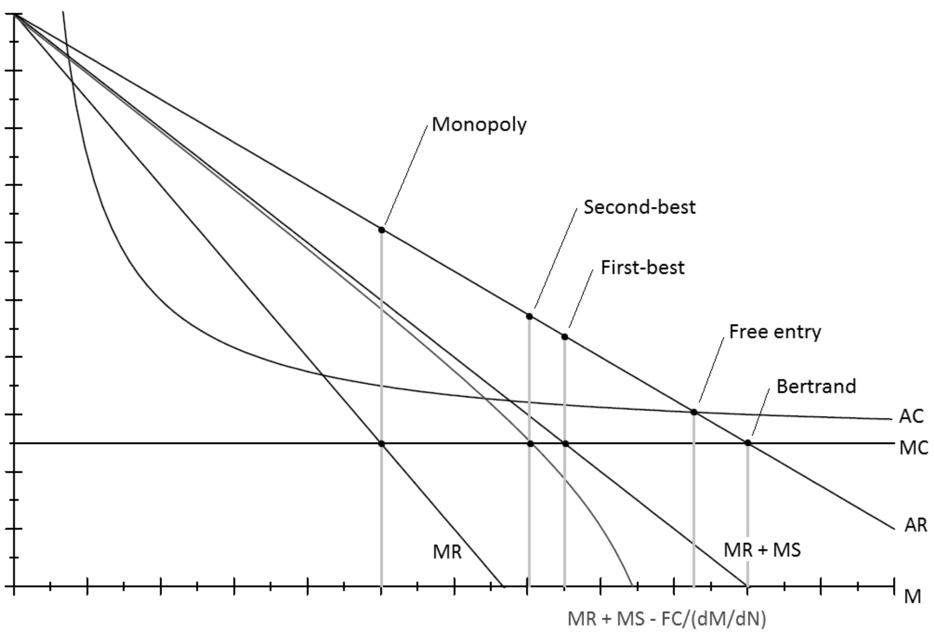
More specifically, when the observed service fee is *below* the socially optimal level, regulating the service fee brokers are allowed to charge will result in a conflict of interest. Raising the fee will bring it closer to its desired level, but it will also worsen the entry distortion because a higher markup for a given fixed cost will incentivize more brokers to enter the market. In this case, it is preferable to regulate broker entry and aim for the social second-best described in proposition 4.3 because this outcome internalizes (although imperfectly) both the price and entry distortion. That is, restricting the number of brokers allowed to operate the market will both raise the service fee and mitigate the entry distortion.

In contrast, when the observed service fee is *above* the socially optimal level, the opposite policy recommendation holds. Restricting entry will mitigate the entry distortion, but will also undesirably further raise the service fee. In contrast, regulating the service fee in this case can again mitigate both distortions at the same time, given that for a lower service fee some brokers will be forced to exit the market.

Figure 2 summarizes the model outcomes under free broker entry, illustrating the case where the observed free entry equilibrium implies that

that the service fee is below the socially optimal fee. The picture shows the first-best social optimum which can only be established should the regulator be able to eliminate all fixed entry costs and regulate the service fee, which coincides with the social optimum depicted in figure 1 above. In addition, the figure also illustrates the second-best social optimum that can be established should the social planner be able to regulate entry, without interfering with the fee setting behavior of brokers once they have entered the market.

Figure 2: First- and second-best social optimum for downward distorted service fees



In the empirical part of this paper, we aim to quantify the first-best and second-best welfare counterfactuals for realistic parameter values derived from the data. For this purpose, the next section starts with presenting a methodology that allows us to identify the relevant model parameters from potentially observable market outcomes in real estate brokerage markets.

4 Identification

4.1 Preferences and bargaining weight

To be able to construct the welfare counterfactuals described in the previous section it is necessary to have information regarding the underlying distributions of buyer valuations and the reservation prices of sellers, which are typically unobserved. The purpose of this section is to describe a possible identification strategy for these underlying distributions when market outcomes, such as the flat fee, the percentage fee, the distribution of transaction prices and the total market share of the brokerage industry, are observed. Imagine, for now, that we have gathered a perfect dataset with an infinitely large number of transactions between different buyers and sellers of the homogeneous housing good[7] where a certain fraction of transactions is carried out with the help of real estate agents. Assume furthermore that we know that the full distribution of transaction prices (both for the market as a whole and those transactions carried out by real estate agents) and the fees charged by real estate agents. The question now is whether we can

[7] Imagine, for instance, that an infinitely large number of pairs of buyers and sellers bargain over an identical house at an identical location at the same time. Although housing is obviously not a homogeneous good (houses and apartments differ in size, location, time of sale, and many other features) the intuition is that we can attribute all observed price variation solely to differences in buyers' valuations and sellers' reservation prices. The methods to cope with the inherent heterogeneity of the housing good are discussed in section 5.1.

retrieve the underlying distributions of buyer valuations and seller reservation prices.

To identify these two preference distributions it is necessary to impose some parametric structure, which will allow us to map a single distribution of observed prices onto the two underlying distributions of buyer valuations and seller reservation prices. With an infinitely large number of buyers and sellers who potentially bargain over a homogeneous housing good it is most natural, and will also prove to be convenient in solving the model, to assume that both buyer valuations and seller reservation prices are normally distributed.[8] More specifically, assume that buyer valuations and seller reservation prices are distributed as follows:

$$b \sim N(\mu_b, \sigma_b) \text{ and } s \sim N(\mu_s, \sigma_s) \tag{29}$$

Given our assumption that transaction prices are the result of an asymmetric Nash-bargain we know that if both buyer valuations and seller reservation prices are normally distributed transaction prices are also normally distributed, by the property of the normal distribution that the sum of two independent normal variables is also normally distributed. It follows that the mean and standard deviation of all transaction prices as a weighted sum of their respective counterparts of buyer valuations and seller reservation prices, that is:

$$\mu_\rho = \beta\mu_b + (1-\beta)\mu_s \text{ and } \sigma_\rho = \beta\sigma_b + (1-\beta)\sigma_s \tag{30}$$

[8] Note that in reality it is typically observed that transaction prices are log-normally distributed. Keep in mind, however, that many of the determinants of house prices (such as living surface) are also log-normally distributed, which implies that when we control for these features, transaction prices might well be normally distributed.

Now, recall from section 2 that the average transaction price of transactions carried out by real estate agents can be written as a function of the bargaining weight and the average and marginal valuation of buyers participating through the brokerage market and that these valuations can be written as a function of the market share of the brokerage industry and the (inverse) distribution of buyer valuations, assuming that the mass of potential buyers and sellers is symmetric $S = B$. More specifically:

$$\bar{\rho} = \beta\bar{b} + (1-\beta)\tilde{b} \tag{31}$$

where $\bar{b}$ is given by expression (7) in which $N^B = M$ and $\tilde{b} = F^{B^{-1}}(1 - M/B)$.

Up to this point we have solely used information regarding prices, but we assumed also to observe the fees charged by real estate agents. Recall from section 2 that the flat fee and commission rate can be written as a function of the average and marginal valuations of buyers and sellers participating through the brokerage market. Again, the average and marginal valuations and reservation prices can be written as a function of the market share of the brokerage industry and function of their respective (inverse) distributions. More specifically:

$$p = \frac{\tilde{b}\tilde{s} - \bar{b}\bar{s}}{\bar{b} - \tilde{b}} \text{ and } t = 1 - \frac{\tilde{s} - \bar{s}}{\bar{b} - \tilde{b}} \tag{32}$$

where $\bar{s}$ is given by expression (8) in which $N^S = M$ and $\tilde{s} = F^{S^{-1}}(M/S)$.

Given that by assumption the market share of real estate agents, the flat fee, the commission rate, the average transaction price of transaction carried out by real estate agents, and the mean and standard deviation of the distribution of all transactions are observed, expressions (30)-(32) constitute a system of 5 equations (p, t, $\bar{\rho}$, μ_ρ and σ_ρ) with 5 unknowns (μ_b, μ_s, σ_b, σ_s and β), which we can solve analytically, with a single unique solution.

4.2 Costs and competitive conduct

Although the previous subsection suggests an identification strategy for retrieving the underlying distribution parameters from observed market outcomes and observed variation in prices it remains to characterize the full market equilibrium under imperfect broker competition and free entry of real estate agents in the first stage of the model. If we are willing to assume that there is free entry of real estate agents in the market (stage 1) and they will enter as long as their (expected) profits are larger than zero, we can extract the constant per-match cost (MC) incurred by each broker when matching buyers and sellers. More specifically, by assuming that profits are equal to zero and subsequently rewriting equation (13), we obtain:

$$MC = AR - \frac{FC * N}{M} \tag{33}$$

which can easily be retrieved when we have information regarding the fixed costs incurred by each broker to operate in the market, the number of matches by real estate agents, the number of brokers in the market, and the average revenue given by expression (16) (which solely depends on the preference parameters identified above). A final step in providing a full characterization of the observed equilibrium is describing the conduct parameter θ in our model. Provided that we have backed out the constant marginal cost per-match in the previous step we can back out θ using proposition 4.1 that describes the optimal private broker behavior. More specifically, by rewriting equation (20), we obtain that:

$$\theta = \frac{AR - MC}{MS + ET} \tag{34}$$

which can be written fully in terms of the previously identified preference parameters and marginal costs.

5 Data and parameter estimates

5.1 Data and solutions to data limitations

In the previous section we proposed a possible identification strategy in a hypothetical world where we have a perfect dataset containing an infinite number of transactions of a homogeneous housing good where, for each transaction, we know the transaction price, whether or not the transaction was carried out by a real estate agent, and if so, the flat fee and the commission rate. For the empirical part of this paper, we have gathered a sample of more than 15000 dwellings that were put up for sale by their owners through one of 135 agencies of a large (Belgian) franchise system of real estate agents between the first quarter of 2011 and the second quarter of 2014. Of these 15000 dwellings slightly over 9000 (=63.5%) were actually sold within their marketing period. Note that our sample contains both properties that were sold and properties that remained unsold, which we will use to address the selection problem that not all sellers participate through the brokerage market. For every property an exhaustive list of characteristics is provided, which will allow us to take into account potential price variation arising from differences in dwelling characteristics. We furthermore observe the total commission charged by the real estate agent for every transaction and its respective components (the respective flat fee and commission rate) when the property was sold throughout its marketing period. Summary statistics of the transaction sample are provided in table 1.

Table 1: Descriptive statistics transactions

Variable	Obs.	Mean	SD	5^{th} percentile	95^{th} percentile
Sold	15 610	0.635	0.481	0	1
ρ	9 926	229 423.64	101 191.16	99 000	415 000
p	9 925	2 796.61	1 911.47	0	6 050
t	9 925	0.030	0.010	0	0.042
$p + t * \rho$	9 925	9 889.32	3 675.61	5 076	16 456
$(p + t * \rho)/\rho$	9 925	0.045	0.008	0.030	0.058
Sq. meters: interior	14 483	185.55	72.54	98.66	328
Sq. meters: lot	15 304	789.74	1 056.90	90	2 500
# bedrooms	15 610	3.237	1.022	2	5
Age	15 515	55.26	34.14	1	113

The table immediately demonstrate that we are far from a hypothetical world in which there exists a homogeneous housing good. The different between the 5^{th} and 95^{th} percentile of observed transaction prices is approximately 316000 euro's, which cannot solely be attributed to differences in buyer valuations and seller reservation prices, but is also due to differences in the underlying characteristics of the respective dwellings. This becomes apparent when looking at the last 4 rows of table 1 where we observe that there are large differences in the living surface, parcel size, number of bedrooms and age of dwellings present in the data. It now becomes crucial to disentangle the observed price variation into price variation arising from heterogeneity in dwelling characteristics and price variation that can be attributed to heterogeneity in buyer valuations and seller reservation prices, which we can use to identify the underlying distribution parameters.

Fortunately, many housing economists have been interested in the (cross-sectional) determinants of house prices and have developed suitable methods. Probably the most well-known method used in the literature is the hedonic pricing method (Rosen, 1974), which is a revealed preference approach that departs from the assumption that the value or demand for an item (in our case house) is determined by the sum of implicit values of its constituent characteristics. Where many housing economists have used the hedonic pricing method to estimate the externalities that arise from, for example, air pollution, we are not intrinsically interested in these estimated implicit values, but use the method purely as a filtering mechanism to disentangle the different sources of price variation. More specifically, our goal is to capture all price variation arising from differences in dwelling characteristics in the model and use the remaining price variation (that is captured by the residuals) to identify σ_ρ. When we estimate the hedonic price model using the following simple regression model (using OLS):

$$\rho_i = \delta X_i + \varepsilon_i \tag{35}$$

We can use the following definitions for the different parameters necessary to identify the underlying distributional parameters:

$$\bar{\rho} = \mu_\rho = \hat{\delta}\bar{X} \text{ and } \sigma_\rho = \sqrt{\frac{1}{N}\sum_{i=1}^{N} {\varepsilon_i}^2} \tag{36}$$

Now, we still face a sample selection problem in the sense that we only observe transaction prices for dwellings that were sold by real estate agents, which implies that our estimates of μ_ρ and σ_ρ in expression (36) are likely biased if we do not account for this. Recall from section 2 that only buyers above the marginal valuation and sellers below a certain reservation price will participate. Although we do not have information concerning transactions that occurred in the outside market, our dataset contains dwellings that were not sold by real estate agents throughout their marketing period, which implies that we can potentially address the selection bias by estimating the well-known Heckman selection model (Heckman, 1979). The Heckman selection model addresses the selection problem (i.e. is the property sold by a real estate agent?) by explicitly modelling it in the first stage and subsequently take it into account by including an additional explanatory variable in the outcome equation (i.e. what is the price of the dwelling?). More specifically, in the first stage, we estimate the following probit model using maximum likelihood estimation:

$$\Pr(S_i = 1|Z_i) = \Phi(\gamma Z_i) \tag{37}$$

Where S_i is a dummy-variable that is equal to 1 when the property is sold, and 0 otherwise. Once we have explicitly modeled the selection process, we can take into account the (potential) selection effect by adding the inverse Mill's ratio (which can be defined as $\hat{\lambda}_i(\alpha_u) = \frac{\varphi(\hat{\gamma} Z_i)}{\Phi(\hat{\gamma} Z_i)}$) as an additional explanatory variable in the outcome equation (stage 2). We thus estimate the following equation in the second stage:

$$\rho_i|z_i^* > 0 = \delta X_i + \delta_\lambda \lambda_i(\alpha_u) + \nu_i \tag{38}$$

Now that we have used the Heckman selection model where our second stage is a hedonic pricing model, we can retrieve the necessary parameters using the following definitions:

$$\bar{\rho} = \hat{\delta}\bar{X} + \hat{\delta}_{\lambda}\lambda(\bar{\alpha}_u), \mu_{\rho} = \hat{\delta} \text{ and } \bar{X}\sigma_{\rho} = \frac{\hat{\delta}_{\lambda}}{\hat{\xi}} \text{ where } \hat{\xi} = corr(\upsilon, \nu) \quad (39)$$

Once we have retrieved the distributional parameters we need additional information to identify the necessary market parameters. In section 4.2 it was shown that the constant per-match cost can be identified when we are willing to assume that we're in a steady state equilibrium where brokers earn zero profits and we have information regarding the fixed costs real estate agents incur to operate, the number of matches carried out by brokers, and the number of brokers that is active in the market.

As in Hsieh & Moretti (2003) we assume that the fixed costs brokers incur is equal to the reservation wage, for which we use the average remuneration per person in the services sector in Belgium in 2012. We retrieve data concerning the average remuneration from the website of the National Bank of Belgium (NBB). In addition, the National Statistics Office (ADSEI) publishes statistics concerning the total number of transactions that were registered in a certain administrative area at a certain time. This, together with the fact that we know that 63.5% of all houses that were put up for sale were sold by brokers allows us to calculate the number of matches carried out by real estate agents. Finally, information concerning the number of real estate agents active in the market which is necessary to identify the constant cost per-match was kindly provided to us by the Belgian professional association of real estate agents (BIV). Since real estate agents are obligated to register with the BIV to be allowed to carry out transactions, but are not necessarily active this proxy for N should be interpreted as an upper bound.

Given that we use N to identify MC and subsequently the competitive conduct parameter θ, it is important to clarify the market definition we use in the empirical analysis. Schaumans & Verboven (2013) use ZIP-codes as their local market definition in their study on local service sectors, among which real estate brokers, in Belgium. The authors suggest, however, that this market definition might not be fully appropriate for brokers (where it do seems appropriate for the other local services studied). In our analysis we therefore define the geographic market at the more aggregate level of the administrative districts. There are 43 administrative districts in Belgium, which largely correspond with a city and its respective agglomeration and rural areas. Table 2 provides some descriptive statistics for the market definition, which will be used in the subsequent analysis.

Table 2: descriptive statistics districts for 2013 (obs = 43)

Variable	Mean	Std. dev.	Min	Max
# firms (BIV)	153.18	197.80	10	1 109
# brokers (BIV)	208.44	285.99	10	1 635
# residences	120 456.69	113 554.75	21 841	548 981
# transactions	2 832.16	2 943.68	373	14 590
Population	258 129.15	244 277.31	46 185	1 154 635
km^2	712.88	406.31	102.18	2 008.67

The descriptive statistics presented in table 2 suggest that large differences exists between different market areas in Belgium. Where the Brussels Capital Region for example houses more than 1600 brokers, there are only 10 registered brokers in Bastogne. We use the average number of real estate agents in a local market as our measure of *N*. The other variables presented in table 2 also display a large degree of heterogeneity, as is to be expected. We furthermore use the (average of) the total number of transactions to calculate the number of matches by real estate agents, that is $0.635 = M/2832$, which implies that $M = 1798$.

5.2 Parameter estimates

The results of the empirical analysis are presented in table 3.

Table 3: parameter estimates

Category	Variable	β	$\hat{\sigma}^b$
Assumed or observed	N	208	
	p	2773.03	
	t	0.0304	
	M/S	0.6358	
	C	48 525.09	
Heckman selection model	μ_ρ	222 761.64***	(9 304.31)
	σ_ρ	53 083.76***	(4 438.05)
	$\bar{\rho}$	242 909.62***	(1 214.13)
System of equations	μ_b	222 103.03***	(9 284.51)
	σ_b	53 433.38***	(4 261.24)
	μ_s	225 171.40***	(8 145.56)
	σ_s	51 804.55***	(4 131.34)
	β	0.7853***	(0.1591)
	$\bar{b}$	253 667.90***	(7 213.86)
	$\tilde{b}$	203 546.56***	(10 592.49)
	$\bar{s}$	194 568.73***	(10 269.59)
	$\tilde{s}$	243 162.20***	(6 993.96)
Zero-profit-condition	c	4 572.30***	(37.01)
Private FOC	θ	0.0210***	(0.0020)

The first part of the table contains information regarding the observed market equilibrium. We observe that in an average local market there are 208 (registered) brokers, who charge an average flat fee of approximately €2800 and an average commission rate of 3.4%. Furthermore, we observe that approximately 63.5% of all dwellings that were put up for sale were sold within their marketing period by the broker. As mentioned previously, we assume that the fixed cost incurred by each broker is equal to the average (yearly) wage observed in the services sector and is equal to approximately €48500.

In the second part of the table we present the main results from our Heckman selection model, where we control for both heterogeneity in dwelling characteristics and the potential selection problem. As was expected, we observe that the average transaction price charged by brokers (represented by $\bar{\rho}$) is higher than the average transaction price in the whole market (represented by μ_ρ). σ_ρ reveals that despite that we control for dwelling heterogeneity, there is a substantial degree of remaining price variation, which we attribute to differences in buyer valuations and seller reservation prices in our model.

Using the information from the first two parts of the table and the identification strategy we proposed in section 4 we can identify the underlying distributional parameters. Our estimates reveal that the mean of buyer valuations is slightly below the mean of seller reservation prices (225171 vs. 222103). Our estimates also reveal that buyers, however, are more dispersed in their valuations, which is represented by the slightly higher standard deviation of the distribution (53433 vs. 51804). Finally, the estimates reveal that sellers have a relatively high bargaining weight of 0.79. The third part of table 3 in addition presents the according marginal and average buyer valuations and seller reservation prices.

The calibration further suggests that the average per-match cost of a transaction is equal to approximately €4600. In a final step we back out the parameter of competitive conduct θ, which is equal to approximately 0.021 in our model. This low estimate suggest that there is strong competition among brokers in setting their service fees.

6 Welfare counterfactuals

This section presents three welfare counterfactuals based the estimated parameter values in the previous section. Firstly, the first-best reported in proposition 4.2, which serves solely as a hypothetical benchmark given that it can never be established in the presence of fixed costs. Secondly, the second-best outcome reported in proposition 4.3 should a social planner that aims to maximize social value be able to regulate entry (N), leaving the private behavior of brokers once they have entered the market unspecified. Thirdly, the outcome of a “naive” social planner that regulates service fees with the purpose to achieve the first-best, neglecting the effects on the entry distortions, which serves to illustrate the importance of the proper choice of policy instrument used to regulate the market.

More specifically, the first counterfactual is obtained by simply substituting the relevant parameter estimates in equation (23) and solving for M^*, setting $N = 0$ (which in terms of welfare is equivalent to setting the fixed costs equal to zero) and subsequently calculating the model outcomes using the relevant equations implied by the model. The second counterfactual follows from expression (26), where the market expansion effect (dM/dN) is simulated through the private first-order condition, given by expression (20). To do this, we assume that competitive conduct follows Bresnahan (1989)’s constant conjectural variations model, where $\theta = (1 + R)/N$, assuming that R is pinned down by the observed free entry equilibrium and is subsequently kept constant, which allows us to simulate the value of M for a broad range of values for N. The third counterfactual results in the same allocation as the first, through expression (23), but all broker profits are now dissipated by free broker entry. Table 4 reports the results.

Table 4: Welfare counterfactuals

Variable	Free entry	First-best	Regulating N	Regulating p and t
t	0.0304	0.0304***	0.0304***	0.0304***
		(0.000)	(0.000)	(0.000)
p	2 773.03	37 680.07***	38 725.51***	37 680.07***
		(3 466.61)	(3 439.42)	(3 466.61)
$\bar{\rho}$	242 909.62***	258 381.64***	258 856.28***	258 381.64***
	(1 214.91)	(1 612.98)	(1 685.36)	(1 612.98)
M/S	0.6358	0.4710***	0.4662***	0.4710***
		(0.0025)	(0.0034)	(0.0025)
N	208	-	13***	1 154***
			(1.1124)	(91.86)
Π	0	55 996 916***	56 271 532***	0
		(4 459 080)	(4 465 584.5)	
CS	90 297 080***	55 063 972***	54 197 740***	55 063 972***
	(7 214 780.5)	(3 952 795.25)	(4 057 950.75)	(3 952 795.25)
ω	90 550 152***	111 060 888***	110 469 272***	55 063 972***
	(7 214 774)	(8 406 931)	(8 459 411)	(3 952 795.25)

The results suggest that welfare generated in the market uder the different scenarios is ranked as follows: first-best $\geq$ regulating N $\geq$ observed outcome $\geq$ regulating p and t. In the hypothetical first-best scenario the social planner can perfectly take into account the distortions from both entry (fixed costs) and the externalities of cross-side participation in buyer demand and seller supply, as reported in the second column. The third column shows, however, that the second-best outcome that could be established by regulating entry is estimated to come very close to the first-best. In contrast, the last column demonstrates that when the social planner would only regulate prices, ignoring the social waste as a result of excessive entry, the resulting price increase would induce a large number of new brokers to enter the market, dissipating all profits, which would result in an enormous welfare loss due to excessive entry ending up in a worse situation compared to observed starting point.

Quantitatively, the results should be interpreted with some caution given that up to this point we have not provided any sensitivity or robustness analysis for the various assumptions made and techniques used to establish the findings. This work is still in progress. In addition, two notes of caution are in place about the results in table 4. Firstly, note that moving from the observed market outcome to the social first-best would induce a large shift in surplus from buyers and sellers to brokers. It is a normative question whether a social planner is willing to allow for such a shift in return for the gains in market efficiency.

Secondly, as already emphasized in the theory section, the welfare recommendations that result from the analysis are highly contingent on whether in the observed market equilibrium the broker fees are below the socially optimal fees, as reported here, or above. In the latter case the policy recommendations reverse and regulating the service fees is likely to be preferable over regulating entry. It is therefore extremely important for a social planner that contemplates to regulate a private brokerage market, to be aware of the “position” of the observed market equilibrium compared to the hypothetical first-best. We are still exploring whether we can derive some reduced form tests from our framework, for example, by exploiting cross local market variation in broker service fees, market shares and sales prices, which could pin down the position of observed market equilibria on the locus between Bertrand and monopoly (broker collusion), without having to impose the structure required now to establish the results.

7 Conclusions

This chapter presented a model of imperfect competition among brokers that operate in a market for real estate and charge a service fee to sellers, that consists of flat and proportional component and is allowed to be imperfectly passed through to buyers through an asymmetric Nash bargain over the sale price of the traded real estate properties. In this setting it is shown that there exists an inverse u-shaped relationship between the degree of price competition among brokers in setting their service fees and social value generated in the market. Thus neither monopoly (broker collusion) nor Bertrand, but an intermediate degree of price competition is optimal from a social point of view. The crucial feature of the model that drives this result is that there is uncertainty about the trading partner buyers and sellers will eventually meet when they enter the market. In this case it is socially efficient (within homogeneous local submarkets) to exclude some buyers with a low willingness to pay and sellers with high reservation prices from the market because their participation decision causes a negative cross-side externality on the more efficient high value buyers and low reservation price sellers that participate through the bargaining process over the transaction price. This externality should be internalized in the service fee charged by brokers, justifying a positive markup over marginal costs.

In addition, in the presence of fixed entry costs and free broker entry, the familiar result that free broker entry always results in excessive entry from a social point of view (e.g. Mankiw and Whinston (1986), Hsieh and Moretti (2003)) is confirmed in the present setting. Both findings combined, that marginal cost pricing is not efficient and that entry is always excessive, has important implications for the effectiveness of different policy instruments that can be used should a social planner want to regulate the market to establish the social optimum. When the observed service fee is *below* the socially optimal level, regulating the service fee brokers are allowed to charge will result in a conflict of interest. Raising the fee will bring it closer to its desired level, but it will also worsen the entry distortion because a higher markup for a given fixed cost will incentivize more brokers to enter the market. In this case, it is preferable the regulate broker entry, given that restricting the number of brokers allowed to operate the market will both raise the service fee and mitigate the entry distortion. In contrast, when the observed service fee is *above* the socially optimal level (for example due to broker collusion), the opposite policy recommendation holds. Restricting entry will mitigate the entry distortion, but will also undesirably further raise the service fee or leave it unaffected. In contrast, regulating the service fee in this case can again mitigate both distortions at the same time, given that for a lower service fee some brokers will be forced to exit the market.

The model was then taken to the data on the Belgian market for real estate brokerage. Based on estimated parameter values derived from the data, several welfare counterfactuals were constructed to evaluate the effectiveness of the different policy instruments that can possibly be used by a social planner. Given that in the observed equilibrium the average service fee is below the social optimum, entry regulation is predicted to yield a welfare gain of about 20%. In contrast, regulating the service fee, neglecting the entry effect, would result is a welfare *loss* of about 40%. These results illustrate the importance of making the proper choice of which policy instrument to use should a policymaker aspire to intervene in a real estate brokerage market.

General conclusions

If there is one general conclusion that can be drawn from the analyses conducted throughout the different chapters of this dissertation it is the following: the conventional social benchmark of marginal cost pricing to evaluate the optimal pricing behavior of firms is not readily applicable to evaluate the optimal pricing behavior of private intermediaries in one-to-one matching markets. Furthermore, where relevant, the proper benchmark to evaluate prices can be significantly above marginal costs. Translated into optimal market structures, this implies that perfect competition among matchmakers will not imply the social optimum. Instead, some market power is likely to be desirable for privately intermediated matching markets to function efficiently.

The underlying economic intuition for this conclusion is twofold. Firstly, the network externalities inherent to a one-to-one matching technology tend to unbalance the social costs of participants entering the market across the two sides of the market. The side of the market where negative own-side congestion externalities among participants are strongest should be priced the highest fee for entering the platform. Or, equivalently, the side that induces the strongest positive cross-side externalities should be charged the lowest fee. The first chapter of this dissertation shows that private matchmakers that charge a flat fee for their service indeed tend to follow this regularity, however, the unbalance in prices will usually be insufficient from a social point of view. That is, the high priced side of the market should be priced an even higher fee and the low priced side an even lower fee.

Given that in practice the fee on the low priced side is typically already restricted at zero, only the former distortion is relevant. Hence, the conclusion that the observed fees charged by many matching platforms are likely to be too low from a social point of view.

Secondly, the inherent feature that there is a lot of uncertainty about the trading partner participants in matching markets will eventually meet when they enter the market provides an additional justification for matching platforms to possess market power. In the presence of bargaining among matched participants this uncertainty implies that it is socially efficient to exclude some participants from the market who are expected to bring little value to the surplus generated by transactions once they are matched. The participation decision of these low value participants causes a negative externalities on the high value participants and these externalities should be internalized in the service fee charged by matchmakers, justifying a positive markup over marginal costs.

Chapters 2 and 4 of this dissertation empirically test for the potential inefficiencies induced by excessive platform competition. Chapter 2 shows that the service fees charged to both buyers and sellers by a large online real estate listing platform are indeed below the estimated socially optimal fees, suggesting that the externality induced by the uncertainty in the matching process is currently insufficiently internalized. Similarly, chapter 4 suggests that service fees charged by real estate brokers are currently below the socially optimal level. Combined with the presence of familiar distortions that might arise from free entry in this market, this result is shown to have subtle implications for competition policy.

Given that matching platforms possess market power, if possible, these platform are likely to charge service fees proportional to an observable outcome of the established matches, like the observed transaction price of a real estate property or the wage of a worker. At least, if the usage of such a proportional fee induces participants to "advantageously select" into the market as formalized in chapter 3. Whether or not the use of such a fee is socially harmful or desirable is ambiguous. It is shown that welfare effect of allowing for proportional fee pricing is closely related to the welfare effect of allowing for third-degree price discrimination in standard product markets.

Apart from illustrating a few special cases for which the conventional wisdoms about market power and competition are potentially violated for the specific case of matching markets, I hope that the analyses in this dissertation will also contribute in a broader sense to how economists are thinking about the functioning of markets in a rapidly changing environment characterized by constant innovations of available information technologies. More specifically, the digitalization of markets, of which online listing markets are only one example, require a different way of thinking about economic efficiency. Marginal and start-up costs have never been lower to set up businesses that potentially attract billions of consumers, suggesting the valuations of network effects have never been higher as they are today. So, different social benchmarks are required to evaluate these type of markets compared to the familiar benchmarks of brick-and-mortar markets. This dissertation may serve to put a few puzzle pieces into their right locations in search of where these benchmarks should be. If so, this will mark progress towards a worthy goal.

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